Public Innovation Policies: An Empirical Analysis of Subsidies and Collaboration

Dissertation
submitted to the Faculty of Business, Economics and Informatics of the University of Zurich

to obtain the degree of
Doktor der Wirtschaftswissenschaften, Dr. oec.
(corresponds to Doctor of Philosophy, PhD)

presented by

Mathias Oliver Hermann Beck
from the Federal Republic of Germany

approved in February 2016 at the request of
Prof. Dr. Dr. h.c. Andrea Schenker-Wicki
Prof. Dr. Ulrich Kaiser

The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 17.02.16

Chairman of the Doctoral Board: Prof. Dr. Steven Ongena

ACKNOWLEDGEMENTS

Writing a PhD thesis is like going on a long journey. During this journey, I have discovered many new and inspiring things, and sometimes I have also faced challenges to overcome. It is worth mentioning here that it would not have been possible to finish or even undertake this journey without the strong support of several people. First and foremost, I appreciate the inspiring exchanges with my doctoral advisor Andrea Schenker-Wicki, Rector of the University of Basel, former Director of the Executive MBA, and Vice Rector at the University of Zurich. I am sincerely grateful to her for accepting me as her doctoral student and providing me with excellent working conditions. Most notably, I am thankful for her unique critical thinking, for her trust in me, and for providing me with the freedom and encouragement to explore new ideas and establish new research topics. Thank you very much for your academic and personal support!

I am enormously thankful to my co-advisor Ulrich Kaiser, Professor for Entrepreneurship at the University of Zurich. He has been an enduring source of expertise and support throughout my thesis work. He was the compass during this journey, and it was my great fortune to work with him. Thank you very much for your scientific and personal guidance! My special thanks must also be given to Uli’s team at the Chair for Entrepreneurship for our exciting discussions, and of course, for sharing time and creating ideas: thanks to Nicole Ehrsam, Martin Murmann, Christian Peukert, Michael Ribers, and Hannes Ullrich!

In addition, I am very thankful to my co-author and mentor Cindy Lopes-Bento, assistant Professor at Maastricht University. It was a privilege and great pleasure to collaborate with her, and my research has benefited greatly from her guidance. Furthermore, I would like to particularly highlight the exchanges with Spyridon Arvanitis at the Swiss Economic Institute (KOF) at ETH Zurich. I appreciate his constructive feedback throughout this thesis. Additionally, I want to thank the team at KOF, namely, Marius Christian Ley, Martin Wörter, Andrin Spescha, and Tobias Stucki, for providing me with a friendly working atmosphere and for their support with the data. I must also thank Beat Hotz-Hart at ETH Zurich for his advice and guidance at the early stage of this journey.

Among my other friends, current and former colleagues at the Department of Business Administration at University of Zurich who provided important stimuli and feedback, I would like to thank Alexandra Arnold, Katherine Caves, María Franco, Simon Janssen, Dirk Martignoni, Stefano Nigsch, Christian Rosser, Stefan Schembera, Lukas Schoenenberger, Bruno Staffelbach, Dominique Vionnet, and Xinhua Wittmann for creating an inspiring working atmosphere and for their valuable support.

Finally, I would like to express my gratitude to my family and friends for their love and support. Particularly, I would like to thank Lorenza for her encouragement and love. My deepest thanks are reserved for my parents Bernd and Heidi, my brother Volker and my sister Anika Maria for supporting me and believing in me.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

CHF	(Confoederatio Helvetica) Franc
CIA	Conditional independence assumption
CIS	Community Innovation Surveys
CTI	Commission for Technology and Innovation
EC	European Commission
ETH Zurich	Eidgenössische Technische Hochschule Zürich (Swiss Federal Institute of Technology in Zurich)
Eurostat	Statistical Office of the European Union
GDP	Gross domestic product
HRM	Human resource management
IPR	Intellectual property rights
IV	Instrumental variable
KOF	Konjunkturforschungsstelle (Swiss Economic Institute)
LR	Likelihood-ratio
NACE	French: Nomenclature statistique des activités économiques dans la Communauté européenne
OECD	Organisation for Economic Co-operation and Development
R&D	Research and development
SBIR	Small Business Innovation Research
SME	Small and medium-sized enterprise
SNSF	Swiss National Science Foundation
U.S.	United States
WIPO	World Intellectual Property Organization
2SLS	Two-stage least-squares

CHAPTER 1

Introduction

Innovation permeates modern society. This perception is easily confirmed through the inspection of nearly all modern company mission statements in which innovation is viewed as the key *modus operandi* for modern organizations. In addition, the public sector has made innovation critical, and countries spend vast amounts of resources to acquire top positions in international innovation rankings such as the Innovation Union Scoreboard managed by the European Commission (EC) or the Global Innovation Index co-published by the World Intellectual Property Organization (WIPO).

Acknowledging the importance of innovation for economic growth and technological change (Aghion & Howitt, 1992; Griliches, 1979; Romer, 1990) as well as recognizing innovation as a crucial source for firms' competitive advantage (Teece, Pisano, & Shuen, 1997), policy makers have developed various policy instruments to stimulate innovation. However, the effects of public intervention are not obvious; for instance, public subsidies could merely crowd out private spending, resulting in no net increase in overall investments in research and development (R&D). This dissertation evaluates two general innovation policies by investigating the role of public R&D subsidies and R&D collaboration focused on fostering innovation. By elucidating these two policies, this thesis' objective is to advance the understanding of the mechanisms through which innovation in the private sector can be stimulated by public innovation policies. Moreover, these new insights will identify key managerial and policy implications, allowing decision makers to improve the effectiveness of these policies, adjust firm innovation strategies, and adjust national innovation policies.

Since the seminal work of Schumpeter, the literature has widely acknowledged R&D and innovation as the main drivers of technological change in society (Dosi, Freeman, Nelson, Silverberg, & Soete, 1988). Firms play a crucial role for the discovery and diffusion of new knowledge and technology (Kogut & Zander, 1992); however, due to the risky and uncertain nature of R&D projects (Knight, 1921) and the non-rival and partially excludable characteristics of knowledge and intellectual property, an under-investment in R&D activities occurs (Arrow, 1962; Nelson, 1959). Firms cannot often fully appropriate the returns of their investments due to spillovers and imitation. Consequently, R&D and innovation activities are subject to market failure (Arrow & Lind, 1970; Martin & Scott, 2000; Romer, 1990).

As a response to the market failures, governments use various instruments to support R&D in the private sector.[1] These instruments include direct subsidies,

[1] In addition to supporting R&D in the private sector, governments can also stimulate R&D in the public sector through direct investments in R&D at universities and state-funded research organizations. These governmental budgets for public R&D largely exceed the financial support for R&D in the private sector.

tax incentives, lower interest rates, and modifications to intellectual property or anti-trust and competition laws. Moreover, many countries have also launched special programs or have established agencies to directly fund R&D and innovation projects in the private sector. For instance, in the United States (USA), the Small Business Innovation Research (SBIR) program has provided financial support for many projects run by small and young innovative firms in the private sector (Audretsch, 2003; Audretsch, Link, & Scott, 2002; Lerner, 2000; Wallsten, 2000). By means of the abovementioned policy instruments, governments attempt to close the gap between the social and the private equilibrium in R&D investment and thereby gain competitive advantages in a global economy.

Governments have increasingly engaged in stimulating R&D and innovation in recent decades. Thus, the EC introduced the objective that EU countries should target spending 3% of their gross domestic product (GDP) for R&D, as formulated in the Lisbon strategy at the European Council in 2000. The EC has renewed this goal in its Europe 2020 strategy, highlighting it as one of the key targets for the European Union and specifying that the investment goals should be attained "in particular by improving the conditions for R&D investment by the private sector" (EC, 2010). Providing an overview of the amount of expenditures invested in R&D activities as a percentage of national GDP, an international comparison conducted by Eurostat reports that certain countries such as South Korea, Finland, Sweden, Japan and Denmark ranked above the 3% level in 2011 (Eurostat, 2013). Switzerland, also one of the leading countries in terms of R&D

intensity, used 2.96% of its GDP in 2012. With respect to Switzerland, approximately two-thirds of the R&D expenditures stems from the private sector (2.05% of GDP) and one-third from the public sector (0.85%) in 2013. With 0.85%, the Swiss governmental R&D expenditures as percentage of GDP is above the EU average (0.73%), but remains below the levels of South Korea (1.09 %, 2010 data), Finland 1.09 %, United States (1.02 %, 2010 data) and Germany (0.90 %, 2010 data).

The discussion of the effects of innovation policies at the micro and macro level remains ongoing (Grilli & Murtinu, 2011; Klette, Møen, & Griliches, 2000). In particular, a deeper understanding of whether policy instruments are able to facilitate successful innovations and enhance social welfare is needed (Martin & Scott, 2000). Additionally, it is important to remember that public interventions do not come without costs. Although this observation is obvious with respect to direct subsidies, it also holds when policymakers intervene in market structures by allowing R&D collaboration. Regarding direct R&D subsidies, it is of general interest to investigate whether taxpayers' money is used in an efficient manner; in addition, interestingly, is whether the public sector is able to effectively orient innovation efforts towards socially desirable outcomes. Answers to the questions issued in this thesis provide additional arguments in the current discussion of the role of the public sector within innovation systems (Mazzucato, 2014).

With respect to direct R&D subsidies, this thesis first addresses the question of whether the direct subsidy scheme under review is effective in confronting the problems related to market failure in R&D investments, and consequently whether this policy helps to increase private investments in R&D activities. Second, this study evaluates the appropriateness of the subsidy policy to stimulate innovations with high degrees of novelty. This specific question concerning where the policy effects are most effective is crucial for policymakers. Although the policy is effective in terms of increasing overall R&D investments, it is interesting to know whether the policy follows the economic rationale that effects should be highest where the market is weakest; and this market failure applies particularly to projects of a more radical nature. Furthermore, with respect to overall economic growth, it is of general interest for policymakers to investigate whether the policy fosters more incremental or radical innovations. These important questions have not been addressed by the literature thus far.

With respect to R&D collaboration, the question remains whether the benefits outbalance the costs related to these joint activities in strategic alliances (Caloghirou, Ioannides, & Vonortas, 2003; Gulati, Nohria, & Zaheer, 2000; Gulati & Singh, 1998; Kogut, 1988; Mowery, Oxley, & Silverman, 1996; Tsang, 2000; Williamson, 1989). On the one hand, by means of R&D collaboration, firms can benefit from greater efficiency in R&D in terms of higher joint financial resources, avoiding the duplication of efforts, complementing their own capabilities, and internalizing spillovers within the consortium (Grimpe & Kaiser, 2010). These activities enable firms to undertake not only larger but also more risky projects. On the other hand, collaborating firms encounter higher risks such as leakage of knowledge due to involuntary outgoing spillovers, unsatisfactory mechanisms of appropriating the returns of joint R&D, and ineffective IP practices, all of which highlight the considerable weaknesses and pitfalls of openness in organizations (Cassiman & Veugelers, 2002; Henkel, 2006; Katila, Rosenberger, & Eisenhardt, 2008).

Consequently, the growing interest in openness within collaborative innovation deserves more attention with regard to the role of inter-organizational structures of knowledge creation and exchange. In-depth knowledge concerning both the opportunities and pitfalls of openness in organizations is needed. Therefore, indeed, the current literature calls for more research to better understand optimal organizational structures that explains how to integrate knowledge from external partners into organizations (Cassiman & Veugelers, 2006; Dahlander & Gann, 2010; Laursen & Salter, 2014; Leiponen & Helfat, 2010; Sampson, 2007; Wallin & Von Krogh, 2010). Specifically, answers to questions such as “What are optimal levels of diversity of collaboration partners in strategic R&D alliances?” and “What are appropriate portfolios of external partners to generate specific types of innovation outcomes?” remain unanswered. In addition, very little is known regarding dynamic adaptation of collaboration networks (Bakker & Knoben, 2014). To advance the knowledge in this field, this thesis investigates first, the effects of diversity of collaboration partner types within strategic alliances on innovation performance; and second, the role of simultaneous and dynamic adaptation of strategic R&D alliances to generate specific types of innovation is studied.

The following three chapters present my contribution to the on-going policy evaluation in the form of an empirical analysis conducted in three papers. The first paper, *Radical or incremental: Where does R&D policy hit?* (Chapter 2), investigates the impact and effectiveness of a public R&D support policy, which directly funds R&D projects in the private sector. The objective of this paper is to contribute to the debate on the returns of public R&D funding (Jones & Williams, 1998; Salter & Martin, 2001) and to analyze whether public money is used in the most effective manner (David & Hall, 2000; David, Hall, & Toole, 2000; Klette et al., 2000). Specifically, this empirical analysis evaluates whether a public subsidy has differentiated effects in regard to incremental or radical innovation, an aspect that has been largely ignored in the literature. The results demonstrate that the Swiss public R&D policy is effective in terms of increasing private R&D investment as well as stimulating innovations of a more radical nature. However, the feature of the policy targeted at encouraging firms to engage in R&D collaboration does not appear to further enhance these effects.

The second paper, *Cooperating with external partners: the importance of diversity for innovation performance* (Chapter 4), explores how diversity in strategic R&D alliances affects firms' innovation performance.[2] This study contributes to the debate on the benefits and downsides of collaboration within strategic alliances (Grimpe & Kaiser, 2010; Laursen & Salter, 2006; Laursen & Salter, 2014). To do so, this study seeks to enlarge the current understanding of specific aspects regarding the relationship between diversity in collaboration partner types and innovation performance. However, the results suggest that higher diversity in strategic alliances is associated with increased innovation performance to a certain degree of diversity. To the best of our knowledge, this is the first empirical study that detects a curvilinear relationship between diversity in collaboration partner types and innovation performance; this indicates decreasing marginal effects. Moreover, our findings demonstrate that, in particular, small firms can benefit more from diversity in their innovation activities.

The third paper, *Innovation outcomes and partner type selection in R&D alliances: The role of simultaneous diversification and sequential adaptation* (Chapter 5), focuses on inter-organizational structures of knowledge exchange and technology transfer within R&D alliances. Contrary to previous literature in this field, which has mainly ignored dynamic aspects of partner type adaptation within R&D alliances, this study accounts for the sequential adaptation of firms' collaboration patterns. In addition, this study seeks to advance the understanding

[2] This paper has been published in a thematic issue on Human Resource Management (HRM) and firm innovativeness in a European context in the European Journal of International Management.

of whether different innovation outcomes, such as radical or incremental innovations, are related to specific structures of inter-organizational knowledge exchange. The empirical findings demonstrate that firms should not remain excessively persistent within the same search activities and that non-adapting collaboration patterns are associated with inferior innovation performance. Moreover, this study highlights the presence of important partner type selectivity and helps to identify appropriate knowledge exchange structures in relation to specific innovation outcomes and firm sizes.

Overall, this dissertation's objective is to advance the understanding of how innovation policies are linked to the generation of innovation in firms. This thesis particularly focuses on the role of direct R&D subsidies and R&D collaboration. From a policy perspective, the new insights should help to explore and identify effective policy designs for R&D subsidies and collaborations to stimulate innovations. From a managerial perspective, this thesis provides meaningful implications for managers in the field of strategic R&D alliances. In particular, this research derives certain interesting insights regarding the effective structures of knowledge exchange with collaborating firms.

CHAPTER 2

Radical or incremental: Where does R&D policy hit?

This chapter is co-authored with Cindy Lopes-Bento and Andrea Schenker-Wicki.

A version of this chapter has been revised and re-submitted to Research Policy.

Abstract: This study investigates the impact and effectiveness of a public R&D support policy. In a policy design that aims at incentivizing radical as well as incremental innovations, we test where the policy impact is highest. While the privately motivated R&D expenditures are significant for both types of innovation, the policy-induced part is significant only for radical innovation. Furthermore, given that the funding agency encourages collaboration, and particularly industry-science collaboration, we further test whether effects are enhanced in collaborating firms. We do not find any evidence pointing to increased effects for the latter.

Keywords: R&D subsidies; collaborative innovation; innovation performance; radical innovation; incremental innovation; policy evaluation; treatment effects.

2.1 Introduction

Innovation is largely acknowledged to be a main factor of a country's sustainable and competitive development (Aghion & Howitt, 1992; Griliches, 1990; Romer, 1990). It is also recognized that due to market imperfections, firms are unlikely to reap all the benefits from their research, leading to underinvestment in R&D in the economy. Therefore, governmental support is a widely accepted means to foster socially valuable innovation.

The concept of market imperfection goes back to Nelson (1959) and Arrow (1962), who state that firms do not invest the socially desired level in R&D efforts due to market imperfections including limited appropriability, lower private than social returns, financial market constraints, high risks about technological standards, high costs and high uncertainty of R&D projects and further forms of negative externalities (Martin & Scott, 2000). The implications of this under-investment in R&D have encouraged policy makers to establish public support mechanisms. In the current paper, we are interested in one particular type of support, namely direct funding for R&D projects. More precisely, we aim at contributing to an on-going debate about the returns of public R&D funding (Jones & Williams, 1998; Salter & Martin, 2001), and in particular about whether public money is used in the most effective way (David & Hall, 2000; David et al., 2000; Klette et al., 2000). In order to do so, we investigate the impact of the Swiss public support policy on outcome characteristics that have so far largely been ignored in this stream of literature. Specifically, we analyze where the policy effect is highest: incremental or radical innovation.

Based on the market failure theory stipulating that under-investment in R&D may be particularly pronounced for more radical innovations because of higher uncertainty linked to such projects, one may expect to see an effect of public support on radical rather than on incremental innovation. Indeed, as shown by Karlsson, Friis, and Paulsson (2004) for instance, there is a higher probability of no returns on investment for more radical innovation when compared to incremental innovation. Likewise, given the riskier nature of such projects, firms may have more difficulties to find external funding (see e.g. Kamien & Schwartz, 1978). As a consequence, given that funding agencies want to stimulate projects, which are socially desirable but would not be undertaken without public support, one would assume that the impact is particularly pronounced for the latter. In the case of the Swiss innovation policy, the goal is however not merely destined at promoting frontier breaking innovation but also to maintain or enhance the competitiveness of the recipient firms, which can be achieved through incremental and radical innovations alike. It is therefore of high interest to know if the created impact is the same for both types of projects or if one type yields more returns than the other.

For the policy maker, such information is crucial in order to optimize the policy structure. Indeed, it is essential to know if the ex-ante project evaluation is appropriate to prevent firms from crowding-out of private R&D expenditures due to public R&D funding. Consequently, in a first step, we investigate the effectiveness of the policy scheme and test if the subsidy leads to higher R&D expenditures. In a second step, we analyze how this policy induced R&D expenditures translate into innovation output, differentiating between radical and incremental innovation. Indeed, even in case of positive input additionality (meaning higher R&D expenditures due to the subsidy), it remains unclear if the policy induced R&D is as productive as the privately induced R&D. Indeed, based on portfolio maximization theory, firms spent their private money first on projects with the highest expected returns. In case of equal (or even higher) productivity, it remains so far indeterminate whether the impact is highest for more radical or more incremental innovation projects. Therefore, a first and main contribution of this paper lies in disentangling the effects of privately invested and publicly induced R&D on innovation outcome, according to the degree of novelty of the products.

Our second contribution pertains to taking into account the firms' collaboration status. It has been proven that R&D collaboration is likely to impact innovation performance due to spillover effects, risk and cost sharing. Collaboration is therefore encouraged by the funding agency. Taking collaboration as well as the type of collaboration into account is therefore crucial as it can advise policy makers on the efficiency of this policy criterion. Within the various collaboration types, the Swiss funding agency particularly encourages collaboration with science. Shedding light on whether collaboration has an important impact on innovation outcome as well as what type of collaboration (i.e. is it mainly science, as encouraged by the agency or do other partners also play a role?) seems therefore particularly relevant in this context. So far, the literature does not advice on this issue, as the impact of the type of partner in a subsidy scheme has not been analyzed in previous papers. Indeed, most papers in the evaluation literature merely account for R&D collaboration (if at all), but do not pay attention to partner diversity.

Thirdly, the present study is undertaken on a representative sample of Swiss firms, which despite being considered an innovation leader among OECD countries, has not received as much attention as many other countries on this subject.

Finally, in contrast to most policy evaluation studies, our analysis also allows drawing conclusions from a managerial perspective. Knowing where the impact of an R&D subsidy is highest in order for them to best adapt grant application efforts to innovation strategies plays indeed an important role. Likewise, knowing whether input and/or output additionality is enhanced through collaboration (as well as through the type of partner) seems essential information for a manager to optimize its R&D project portfolio.

We base our analysis on a representative firm-level data-set covering the period from 1999 to 2011 of the Swiss innovation survey. We find that, on average, the receipt of an R&D subsidy translates into higher R&D investment. In terms of innovation performance, we find that the impact of public support is only significant for radical innovation, while no impact of policy-induced R&D is found for incremental innovation. Privately financed R&D on the other hand is significant for both types of innovation. In terms of collaboration, we do not find evidence that the impact of the policy is improved through collaboration. We can thus conclude that while the Swiss public R&D policy is efficient in terms of stimulating R&D investment and innovation performance of more radical nature, the current tendency of encouraging R&D collaboration does not seem to enhance such effects.

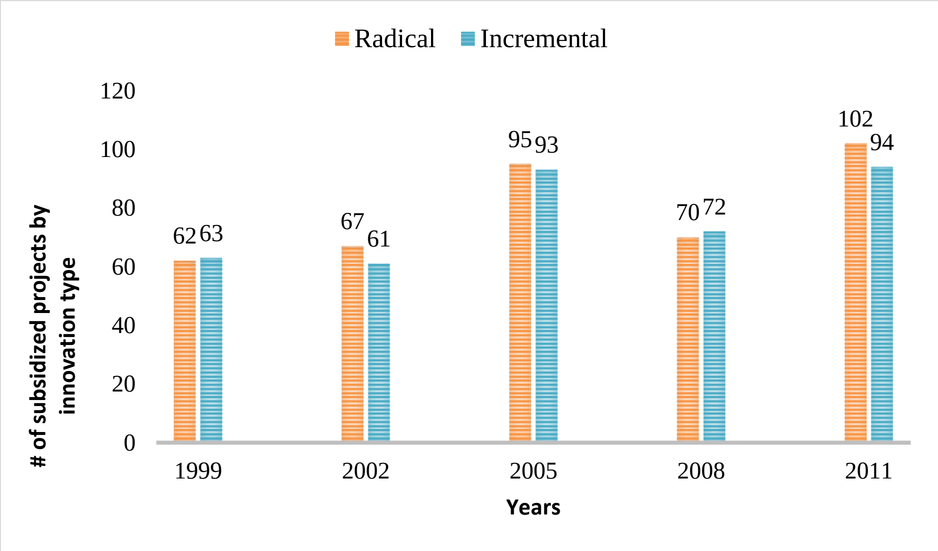
2.2 Overview of the theoretical background and previous studies

Many countries have launched innovation policy programs to promote national innovativeness and competitiveness. An outstanding performance in R&D and innovation activities is considered an important factor not only for economic growth but also for a sustainable economic perspective in terms of employment, ecology and education for a modern knowledge society. In Switzerland, public funding of R&D has increased by 5.3% between 2000 and 2010. In 2010, the financial budget for appropriations or outlays dedicated to R&D covers an amount of 4.6 billion CHF, which corresponds to 0.81% of the country's GDP. In an international comparison (measures from 2008), Switzerland holds the eleventh rank of 31 OECD countries with public R&D funding corresponding to 0.73% of the country's GDP. The United States (1.02%) and Finland (0.98%) are on the top positions of the public funding per GDP ratio (FSO, 2012).

In Switzerland there are two major R&D funding agencies providing public grants for R&D programs and projects—the Swiss National Science Foundation (SNSF) and the Commission for Technology and Innovation (CTI)—with a total budget of 1.0 billion CHF in 2010. While the SNSF is mainly in charge of providing public grants to R&D projects or programs conducted by public research institutes or by individual researchers, the CTI is the responsible funding agency for R&D projects in the private sector, with a total budget of 118 Mio CHF in 2010. As a consequence, the subsidies under review in this study mainly stem from the CTI.

The subsidy scheme is not based on calls for proposals, but firms can apply with R&D projects all year long. Likewise, there are no restrictions in terms of technology fields supported by the agencies. Nonetheless, the CTI has the general goal to stimulate innovation in SMEs and encourages joint R&D activities between private companies and public research institutes. The focus of the policy is two-fold: on the one hand, the agency provides support for applied and market-oriented R&D projects which lead to the generation of improved technologies and products to strengthen the country's innovation position (CTI, 2011). On the other hand, the CTI also supports high risk but promising, cutting-edge technologies. As can be seen in Figure 1 on the subsidy distribution by innovation type, there is hardly any difference between the numbers of subsidies going to firms with radical or incremental innovation output.[3]

Figure 1: Subsidy distribution by innovation type



Source: Own calculations. Data derived from the Innovation survey conducted by the Swiss Economic Institute (KOF).

Applicant firms have to provide a detailed description on the project's impact and a clear business and financial plan. The ex-ante evaluation is done by external and internal referees, which evaluate the expected effectiveness of the R&D projects. In 2010, 780 projects were evaluated, and 343 (44%) projects have been retained for public support (CTI, 2013).

[3] The distribution of subsidies across sectors and firm size classes can be found in Appendix 2.8.1, Table 8 and Table 9.

In case of a positive evaluation, the firm receives a subsidy in form of a matched grant, where the public funding typically covers up to approximately 50% of the expected costs (CTI, 2011, 2013). That is, the recipient firm always faces a co-financing clause by which is it held to finance half of the project costs from private resources. In 2010, 667 firms are involved in co-funded R&D projects, among which almost three quarters (74%) were SMEs (CTI, 2013). The average project duration is of 20 months and the average project size amounts to 682.2 thousand Swiss francs.[4] As can be seen by Table 1, the number of subsidized firms has remained very stable over the period under review.

Table 1: Subsidy distribution over survey period 1999-2011.

Year	Number of firms	Percentages of non-subsidized firms	Percentages of subsidized firms
1997-99	1,140	90.70	9.30
2000-02	1,370	93.80	6.20
2003-05	1,310	90.61	9.39
2006-08	1,124	91.46	8.54
2009-11	1,140	88.07	11.93
Total	6,084 (100%)	91.03 (on average)	8.97 (on average)

[4] Data about project duration is provided by ARAMIS, a database of the Swiss federal administration.

2.3 Our research question in light of recent literature

2.3.1 The impact of R&D support

Empirical evidence on R&D subsidies is common in the literature to date. In terms of input additionality, it has been shown that the null hypothesis of full crowding out can be rejected in the vast majority of cases. In other words, most studies find that firms receiving public support invest more in R&D than if they would not have been supported. The subsidy hence reaches its goal of stimulating R&D investment. Indeed, Hall and Maffioli (2008) have found that in empirical literature since 2000, total crowding out effects were only found for the US Small Business Innovation Research (SBIR) program, analyzed by Wallsten (2000).[5]

In terms of output additionality, evidence confirms that subsidies have a positive impact on innovation performance, as measured for instance by patent outcome (see e.g. Czarnitzki and Hussinger (2004) or Czarnitzki and Licht (2006)) or novelty sales (see for instance Czarnitzki and Lopes-Bento (2014) for a sample of German firms or (Hottenrott and Lopes-Bento (2014a) for a sample of Belgian firms). In a recent study on Swiss firms, Arvanitis, Donze, and Sydow (2010) found evidence for improved innovation performance of supported firms with respect to six different measures of innovation performance.[6]

---

[5] See Czarnitzki and Lopes-Bento (2013) for an overview on relevant recent empirical studies; and Cerulli (2010) for a critical overview on the different applied methods.

[6] Their respective outcome variables include: Importance of introduced innovations from a technical point of view, Importance of introduced innovations from an economic point

Papers distinguishing the productivity effects of privately respectively publicly funded R&D remain limited to date. Even though Madsen, Clausen, and Ljunggren (2008) suggest that input and output additionality are interrelated, to the best of our knowledge only Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006) and Hottenrott and Lopes-Bento (2014a) consider this disentanglement and find a positive impact of publicly induced R&D investment on patenting activities in German firms and novelty sales in Belgium firms respectively. The latter do not differentiate between the degrees of novelty in innovation sales though.

Compared to the above studies, the current analysis further considers the disentangled investment in light of the degree of novelty of the innovation outcome. As stipulated by Garcia and Calantone (2002), the difference between incremental and radical innovation is crucial. While radical innovations have the potential to push the technological frontier of a firm or even sector and may allow a firm to enter new markets, incremental innovations may be considered the “lifeblood of an organization” (p. 123) for mainly two reasons: “first as a competitive weapon in a technologically mature market; and second, because streamlined procedures based on existing technology can help alert a business in

---

of view, Percentage reduction of average variable production costs due to process innovation, Sales of significantly improved or modified (already existing) products as a percentage of total sales, Sales of products new to the firm or to the market as a percentage of total sales, Sales of products new to the market worldwide as a percentage of total sales.

good times to threats and opportunities associated with the shift to a new technological plateau" (Johne & Snelson, 1988, p. 115). Distinguishing these two types of innovation therefore seems an important characteristic in a policy evaluation context, as it allows targeting the policy as necessary.

While more radical innovation has a high potential to have a fundamental impact on firm performance, it is also often involved with higher costs and higher risks. It may thus well be that projects of radical nature are less likely to be undertaken by firms left to themselves as firms have to be willing to bear the inherent risk of this endeavor and also have to be able to provide the necessary funding. Since the assumption is that firms are often risk-averse and financially constrained, this could lead to a sub-optimal allocation of radical vs. incremental innovation (Arrow & Lind, 1970).

Hence, it is difficult to predict ex-ante where the policy effect will be highest and whether the selection process of the funding agency is efficient in light of the type of innovation in which the additional investment will be destined to.

2.3.2 The impact of R&D collaboration

It has long been acknowledged that R&D collaboration plays an important role, for the type as well as the success of innovation projects. Allowing limiting outgoing spillovers by internalizing them to the research consortium and providing access to complementary know-how and resources of partnering firms, it has been shown that R&D collaboration can enhance private R&D activities substantially (see for instance D'Aspremont & Jacquemin, 1988; DeBondt, 1997; Kaiser, 2002; Kamien, Muller, & Zang, 1992; Katz, 1986).

Subsidized collaborative R&D has received less attention though in the empirical literature so far. Exceptions are Sakakibara (2001) and Branstetter and Sakakibara (2002) who analyzed Japanese government-sponsored R&D consortia. Both studies found evidence that participating firms have higher R&D expenditures as well as more patents. Further, Czarnitzki, Ebersberger, and Fier (2007) apply a matching estimator in a multiple treatment setting, analyze the effects of R&D collaboration and public R&D funding on R&D per sales and patent outcomes for Germany and Finland and find that collaboration has positive effects. Finally, Hottenrott and Lopes-Bento (2014a) find that in a sample of Belgian firms, international collaborating firms have a higher subsidy treatment effect than nationally or non-collaborating firms.

The aspect of various partner types (i.e. horizontal, vertical or collaboration with science) within a subsidy scheme has so far not yet been analyzed in the evaluation literature though. However, since funding agencies often encourage industry-science links, having evidence on the impact of subsidized projects with specific partners would allow shedding new light on the efficacy of such policy criteria. Indeed, studies have acknowledged the role played by various partner types and the impact they may have on innovation performance (Belderbos, Carree, Diederen, Lokshin, & Veugelers, 2004a; de Faria, Lima, & Santos, 2010;

Faems, Van Looy, & Debackere, 2005; Kaiser, 2002). However, to date we don't know yet about their impact in light of a publicly co-financed subsidy scheme.

Before assessing the role of collaboration in an R&D subsidized context empirically, it is important to emphasize that collaboration may also be linked to certain risks. For instance, collaborating firms run the risk of free riding of one of the partners, disclosing of the firms' secrecy or weak IPR systems, rendering the appropriation of the returns of joint R&D projects difficult. Indeed, to be able to fully benefit from collaboration, a firm needs to build up specific competences and maintain a fruitful level of absorptive capacity to manage and coordinate collaborations efficiently and effectively. Otherwise, outgoing spillover effects might be higher than incoming spillover effects for some partners of the consortium, leading to the costs of collaboration being higher than the gains. Finally, incomplete contracts resulting from poor bargaining and costs of disclosure that are inherently linked to collaboration may render collaborative R&D costly if collaboration exceeds a certain threshold (Beck & Schenker–Wicki, 2014; Hottenrott & Lopes-Bento, 2014b). While such caveats are always true, they may be particularly pronounced for subsidized collaboration agreements insofar that firms may conclude collaborative R&D agreements to increase the chances of being retained for public support rather than because of true complementarity of skills or know-how between partners. Furthermore, coordination costs may be higher in the case of subsidized collaboration agreements due to monitoring or reporting duties of the funding agency.

The present analysis precisely aims at measuring such effects, by taking the type of partner within the subsidy scheme into account, thereby advising whether encouraging R&D collaboration overall, and industry-science links in particular, is an efficient policy criterion.

2.4 Methodological approach and estimation strategy

2.4.1 Input additionality analysis

In the first step of our analysis, we are interested in estimating the treatment effect of the R&D subsidies on firms' R&D investments. As subsidies are not randomly distributed, one has to take the selection into the funding program into account in the evaluation analysis. Indeed, subsidized firms might differ from non-subsidized firms in important characteristics, and therefore the selection into the treatment has to be taken into account (Grilli & Murtinu, 2011; Heckman, LaLonde, & Smith, 1999; Imbens & Wooldridge, 2008). While several modern econometric techniques exist allowing to address such a selection bias, our study applies a non-parametric nearest neighbor propensity score matching, as this is the most adequate method for the data at hand in this study (to be presented in the next section) (Angrist, 1998; Gerfin & Lechner, 2002; Lechner, 1999; Smith & Todd, 2005).

The econometric matching allows to directly reply to the question of how much a subsidized firm would have invested in R&D if it would be in a counterfactual situation of not having received public support. Given that this counterfactual situation is never observable, it has to be estimated. Based on the assumption that we observe all the important characteristics driving the selection into the treatment (that is, provided that the conditional independence assumption (CIA) is respected (Rubin, 1977)), we can approximate this counterfactual situation by firms having the same (or very similar) characteristics than the subsidized firms, but have not received any support. In order to find such similar "twins", we balance the subsamples of subsidized and non-subsidized firms according to the probability of receiving a subsidy. Based on a probit estimation, we obtain the conditional probability of receiving a subsidy in a single index, the propensity score. That means that we compare subsidized firms with firms that had the same probability of being subsidized, but did not receive public support. Based on this index, we apply a nearest neighbor matching estimation and use for each subsidized firm the single nearest neighbor to estimate the counterfactual situation (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1985). On top of matching on the propensity score, we further require firms of the treated and control groups to belong to the same year and the same industry.

The average treatment effect on the treated is estimated as follows:

$$\alpha_{ATT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(R\&D_i^T - \widehat{R\&D}_i^c\right) \tag{2.1}$$

where $R\&D_i^T$ indicates R&D expenditures of treated firms and $\widehat{R\&D}_i^c$ *the* counterfactual situation, i.e. the potential outcome that would have been realized if the treatment group ($S=1$) had not been treated. $S \in \{0,1\}$ indicates the receipt of a subsidy and N^T the number of treated firms.[7]

2.4.2 Effectiveness of the R&D policy

In a second part, we turn to the analysis of how the additional policy-induced R&D investment translates into innovation performance. More precisely, provided that we find positive input additionality, we want to know whether the publicly induced R&D investment is as productive as the privately invested R&D expenditures, and if such impacts differ between radical or incremental innovations.

Taking into account that not every firm in our sample has new product sales in each period, our outcome measures are characterized by a corner solution around zero (Tobin, 1958). For our analysis, we therefore use Tobit models to give point to these censored dependent variables.

[7] Finally, in order for the matching to be possible, enough common support is needed between the sample of treated firms and the sample of potential control firms. To this end, the samples of treated and control firms need to have enough overlap in terms of probability of receiving a subsidy. Observations on treated firms with probabilities larger than the maximum and smaller than the minimum of the potential control group will therefore be deleted.

In order to disentangle public from private R&D investment, we estimate the policy impact at the firm level in the same fashion as Hottenrott and Lopes-Bento (2014a) as follows:

$$\alpha_i^{TT} = R\&D_i - \widehat{R\&D}^C{}_i \tag{2.2}$$

where $\widehat{R\&D}^C{}_i$ is equal to R&D intensity for the counterfactual firms. Indeed, for non-subsidized firms for which α_i^{TT} is equal to zero, $\widehat{R\&D}^C{}_i$ corresponds to their private R&D investment. For subsidized firms, the individual treatment effect corresponds to the difference of the treated firm and its counterfactual situation, namely its unsubsidized twin. This provides the estimated treatment effect by firm, allowing estimating the policy-induced investment separately from the privately invested money on subsequent innovation performance. Furthermore, it allows taking the size of the subsidy into account.

The Tobit model for $Radical_i$ can then be estimated as follows:

$$Radical^*{}_i = X'{}_{i,t-1}\beta + \epsilon_i, \epsilon_i \sim i.i.d.N(0,\sigma^2) \tag{2.3.1}$$

$$Radical_i = \begin{cases} Radical^*{}_i \; if \; X'{}_{i,t-1}\beta + \epsilon_i > 0 \\ 0 \; otherwise \end{cases} \tag{2.3.2}$$

where $Radical_i$ is the non-negative observable innovation performance variable, capturing radical innovation at the firm level. $Radical_i$ corresponds to the latent dependent variable $Radical^*{}_i$ if latter is above zero and to zero otherwise. The model on the latent dependent variable, $Radical^*{}_i$ is estimated by a parameter vector β, and a vector of firm characteristics $X_{i,t-1}$. The latter relationship is affected by a normally distributed error, to capture randomized firm influences. The model on incremental innovation is estimated analogously.

In order for the estimates of a Tobit estimation to be consistent (see Wooldridge, 2010, pp. 680-687), homoscedasticity is required. Given that we found evidence for heteroscedasticity based on a Likelihood Ratio test, we estimate heteroscedastic robust Tobit models by maximum likelihood. Therefore, we replace the homoscedastic standard error term σ with $\sigma_i = \sigma\exp(Z'\alpha)$ in the likelihood function, modeling for group-wise multiplicative heteroscedasticity by including firm size and industry dummies. Accounting for the fact that our estimates for R&D investments (α_i^{TT}, $\widehat{R\&D^C}$) are estimated values for the treated firms, ordinary standard errors would be biased. We thus correct our standard errors by conducting a bootstrapping procedure.[8]

2.5 Data and model specification

2.5.1 Data

For the empirical analysis, the study uses a large-scale sample of Swiss firms derived from five waves (1999, 2002, 2005, 2008, and 2011) of the Swiss innovation survey, covering the years 1997-1999, 2000-2002, 2003-2005, 2006-2008 and 2009-2011. The Swiss innovation survey is a postal survey conducted

[8] We bootstrap the entire procedure (inclusive of the matching) 150 times, allowing us to estimate how the sample mean of our actual sample varies due to random sampling.

by the KOF Swiss Economic Institute at the ETH Zurich, and corresponds largely to the European Community Innovation Survey following the OECD guidelines (OECD, 1992). Our data set provides us with a representative sample, covering both manufacturing and service industries. The data set contains detailed information on firms' R&D and innovation activities, performance measures, subsidy receipts and other firm characteristics. The response rates from the surveys are: 33.8% (1999), 39.6% (2002), 38.7% (2005), 36.1% (2008), and 35.9% (2011). After eliminating missing values and limiting our sample to innovating firms only, we are left with 6084 observations from 3552 different firms, out of which 546 received a subsidy.

2.5.2 Dependent variables

Our analysis is separated into two main parts. For the treatment effects analysis, our outcome variable reflects the firms' R&D investment, measured as the R&D expenditures to total turnover (*RDINT*). In the second part, following Meuer, Rupietta, and Backes-Gellner (2015), our outcome variables indicate radical innovation performance (*RADICAL*), measured as the sales share of radical innovative products and incremental innovation performance (*INCREMENTAL*), measured as the sales share of significantly improved products.[9]

[9] We follow Meuer et al. (2015) for the definition of radical and incremental innovation. Using the same dataset as we use in our study, the authors define new products—to the market or the firm—as radical innovation and significantly improved products as incremental innovation.

2.5.3 Main explanatory variables

The receipt of a subsidy is indicated by a dummy (*PUBSUB*) equal to one for subsidized firms and zero otherwise. Privately invested R&D expenditures and policy-induced expenditure are denoted by $\widehat{R\&D}^{C}$ and α_i^{TT} respectively.

As an important part of our setting is to analyze the role of R&D collaboration, we account for various collaboration partners. A dummy variable (*RDCOOP*) simply indicates if a firm is engaged in R&D collaboration. We then distinguish between vertical (*CO_VERT*), horizontal collaboration (*CO_HOR*), and collaboration with science (*CO_SCIE*).

2.5.4 Other control variables

We further control for a set of variables, which might influence the selection into public funding and/or drive innovation performance.

Other studies using this definition include for instance Ettlie, Bridges, and O'keefe (1984), who define radical innovation as being "new to the adopting unit and new to the referent group of organizations […] is sufficient to warrant the designation rare or radical, as opposed to incremental" (p.683). Garcia and Calantone (2002, p.122) stipulate that: "A failure to find discontinuity in technology and marketing strategies within a firm, should automatically exclude the product from being considered radical." Hence, a technology new to the firm, introducing a discontinuity within the firm, should according to the typology of this paper be viewed as radical, while an improvement not causing a discontinuity at the firm level qualifies as incremental.

Having received a subsidy in the past might demonstrate existing competence and capabilities of the applicant and hence might influence the agency to select this firm again for a grant. We thus control for previous subsidies, where *PAST_SUBSIDY* equals one if a firm has received a subsidy in the past three years. Existing R&D capabilities may also be reflected in existing patents at the firm level. Indeed, patents may be a valid signal of previously successful R&D engagement. Consequently, we include a variable (*PAT_EMPL*) measuring successfully approved patents per 1,000 employees to avoid potential multicollinearity with firm size. We further control for firm age (*FIRMAGE*) and (the log of) firm size (*LNFIRMSIZE*), as these are important characteristics in the funding scheme of the agency. Additionally, we take a non-linear relationship into account and control for the squared term of the two previously mentioned variables (*FIRMAGE2, LNFIRMSIZE2).*

Labor productivity might also influence the agency in the approval process, as it can be seen as an indicator for high firm competitiveness. We include the natural logarithm of the sales share per employee (*LNLABPROD*). As stated by Cohen and Levinthal (1990), absorptive capacity is essential to integrate new knowledge. We therefore control for share of workforce with tertiary education in total employment (*EMPACA*). We further control for the fact that a firm belongs to a foreign group (*FOREIGN*). Subsidiaries with a foreign parent may be less likely to receive subsidies, because the parent may prefer to apply in its home country. Likewise, funding agencies may have a preference for local firms.

Furthermore, foreign parents with local subsidiaries are typically larger firms and may therefore not be the priority target of the funding agency, as SMEs generally constitute the main target group. It could, however, also be that firms belonging to a group may look attractive to a funding agency as the group membership possibly promises knowledge spillovers and thus economies of scope from the R&D process that go beyond national borders. It is thus unclear whether having a foreign parent plays favorably or not in receiving a subsidy from a Swiss funding agency. We take foreign market activities of a firm into account by controlling for its export activities. Highly export orientated firms might be more innovative, and hence more likely to apply for a subsidy. Export activities are measured by the export share to total turnover (*EXPORT*).

In addition, we account for the level of general technological potential of a firm (*TECHPOT*) indicating the level of scientific and technological knowledge available to the firm for conducting innovation activities. *TECHPOT* is measured on a five point Likert-scale, where five indicates a high technological potential of the focal firm. Finally, five survey-year dummies and seven industry sector dummies complement our set of control variables.

2.5.5 Timing of variables

As mentioned above, each wave of the survey covers a three-year period. In order to avoid endogeneity between the dependent variables and the covariates to the largest extent, we employ lagged values wherever possible. For instance, suppose the dependent variables are measured in period *t*. Then variables such for instance as employment or export are measured at period *t-1*.

Information on variables that are assumed more stable over time, such are for instance being part of a group, are only available for the entire 3-year-period, i.e. *t-2* to *t*. For instance, "Did your firm belong to a group during the period 2003-2005?" We consider age as truly exogenous and hence it is measured in period *t*.[10]

2.5.6 Descriptive statistics

Table 2 presents descriptive statistics of the variables in our analysis. Industry and size class distribution of our sample are displayed in Table 8 and 9 in Appendix 2.8.1. As presented in Table 2, significant differences in the means of almost all variables between the subsidized firms and the non-subsidized firms exist. For instance, on average, subsidized firms are more likely to have experience in the past with subsidies, are slightly larger, have more approved patents per employee, have a higher likelihood belonging to a foreign group, have a higher educated workforce, are more export-oriented, have a higher technological potential, and engage more in R&D collaboration. Notably, they do not differ in firm age and labour productivity. With respect to the outcome variable, in alignment with our expectation, subsidized firms have on average higher R&D investments. However, at this point, we do not know how much of these additional R&D expenditures are induced by the subsidy or are due to other firm characteristics.

[10] Refer to Arvanitis, Ley, Seliger, Stucki & Wörter (2013) for more information on the structure of the survey.

Table 2: Descriptive statistics on innovating firms.

	Unsubsidized firms, N = 5,538		*Subsidized firms, N = 546*		*Results of t-tests on mean differences*
Variables	Mean	Std.dev.	Mean	Std.dev.	
			Covariates		
PAST_SUBSIDY	0.016	0.124	0.203	0.403	***
FIRMAGE	65.2	42.2	68.2	54.0	
FIRMAGE2	6034.9	10583.9	7562.7	21140.4	*
LNFIRMSIZE	4.269	1.410	4.930	1.515	***
LNFIRMSIZE2	20.215	13.411	26.597	16.368	***
PAT_EMPL	12.904	143.565	31.965	90.542	***
LNLABPROD	12.509	0.752	12.505	0.650	
FOREIGN	0.158	0.365	0.200	0.400	**
EMPACA	5.760	11.413	11.875	16.974	***
EXPORT	25.498	34.307	51.031	38.591	***
RDCOOP	0.186	0.389	0.639	0.481	***
TECHPOT	2.788	1.144	3.484	0.977	***
			Outcome variable		
RDINT	1.400	3.894	5.747	13.606	***

2.6 Empirical analysis and discussion

2.6.1 Average effect of public funding on subsidized firms

As described above, we employ a matching estimation to identify the average treatment effect of public R&D grants on the treated firms. To be able to apply the matching estimator, we need to predict the probability of receiving public R&D funding. Therefore, we estimate a probit model on a subsidy receipt incorporating important characteristics for the selection into the funding scheme. As can be seen in Table 3, with the exception of firm age, patents per employee, and being member of a foreign group, all our covariates are important drivers for the selection into the treatment.

Table 4 presents the results of our econometric matching estimation. We can see that all our covariates are well balanced after the matching. This points to the fact that our matching was successful and that we found a close neighbor for each of our treated firms. The only variable that remains statistically significant is the outcome variable. We can thus attribute this difference to the treatment and can conclude that, in line with the literature, full crowding out can be rejected.

Table 3: Probit estimation on the probability of receiving a subsidy.

Variables	Coefficient	Standard errors
PAST_SUBSIDY	1.149***	(0.100)
FIRMAGE	-0.001	(0.000)
FIRMAGE2	0.000	(0.000)
LNFIRMSIZE	0.142*	(0.090)
LNFIRMSIZE2	-0.004	(0.010)
PAT_EMPL	0.000	(0.000)
LNLABPROD	-0.217***	(0.040)
FOREIGN	-0.082	(0.070)
EMPACA	0.013***	(0.000)
EXPORT	0.004***	(0.000)
RDCOOP	0.770***	(0.060)
TECHPOT	0.148***	(0.030)
No. of observations	6084	
Log likelihood	-1392.4211	
Joint significance of industry dummies	$\chi2(6) = 19.92$***	
Joint significance of survey year dummies	$\chi2(4) = 27.01$***	

Note: The model includes a constant, industry and survey year dummies (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

In order to take a potential selection on unobservables into account, we test the robustness of our matching estimation by conducting an IV regression. The results of the IV regression as well as the choice of our IVs are presented in detail in Appendix 2.8.2 (Table 10). Conclusions remain unchanged even if we allow for a selection on unobservables.

Table 4: Average treatment effect of public R&D funding.

	Selected control group, N=530		*Subsidized firms, N=530*		*p-value of t-tests on mean differences*
Variables	Mean	Std.dev.	Mean	Std.dev.	
			Covariates		
PAST_SUBSIDY	0.145	0.353	0.179	0.384	0.195
FIRMAGE	69.8	47.2	68.4	54.1	0.707
FIRMAGE2	7097.0	11617.0	7605.1	21382.6	0.656
LNFIRMSIZE	4.765	1.452	4.891	1.485	0.234
LNFIRMSIZE2	24.815	14.577	26.120	15.855	0.228
PAT_EMPL	20.623	54.565	28.963	79.044	0.072
LNLABPROD	12.483	0.668	12.496	0.648	0.784
FOREIGN	0.183	0.387	0.198	0.399	0.591
EMPACA	12.578	19.054	11.259	16.303	0.311
EXPORT	49.026	38.315	50.302	38.537	0.644
RDCOOP	0.632	0.483	0.628	0.484	0.913
TECHPOT	3.453	1.015	3.457	0.974	0.958
			Outcome variable		
RDINT	3.453	5.859	5.698	13.717	0.001

Note: *** (**, *) indicate a significance level of 1% (5%, 10%). 16 observations are lost because of the common support condition.

2.6.2 The impact on innovation performance

In the following section, we turn to the analysis on innovation performance, as measured by the sales share of radically and incrementally new products respectively. Before turning to the analysis, we provide some additional descriptive information on the variables that have not been used so far.

More precisely, in Table 5 we show the distribution of radical and incremental innovation sales, as well as the distribution of policy induced and privately motivated R&D investment. We can see that the average sales share from radically new products is of 14.4% in our sample. Incremental innovations account for 16.7% of the total turnover of the firms in our sample. The average treatment effect amounts to 0.13%, while the private R&D investments corresponds to 1.86%. Furthermore, we see that even though the average treatment effect is positive, we have also some firms that experience a negative additionality. Specifically, as shown by Table 6, 43% of the treated firms have a negative alpha. In other words, for 43% of the firms, the R&D expenditures did not go up, but to the contrary, the firms spent less money on R&D even though they have received a subsidy. This can happen in case a project gets abandoned for instance, and all the related expenditures get cancelled as a consequence. While this may seem high, very similar results have been found for subsidized firms in Belgium, where 43,5% of subsidized firms experienced a negative additionality (see Hottenrott et al., 2014). Roughly 9% of the subsidized firms have an additionality of zero, meaning that they have spent exactly what they have received from the government, thereby not creating additional R&D expenditures in the economy. Finally, the lion's share of the subsidized firms (46.5%) has a positive additionality, as one would expect by the way the policy is constructed. In different words, these firms have respected to co-financing clause and have added private money to increase their overall R&D expenditures. Finally, 0.1% have an additionality above 50, which means that they invest over half of their turnover in R&D. While this may seem unlikely, it should be noted that it concerns only 5 firms, two of which are very small (6 employees and 9 employees respectively). For such small firms, very high additionalities are not surprising.

Table 5: Additional descriptive statistics.

Variables	Observations	Mean	Std.dev.	Min.	Max.
RADICAL	4,862	14.406	18.139	0	100
INCREMENTAL	4,862	16.706	19.654	0	100
α_i^{TT}	4,862	0.127	3.899	-52.134	100.0
$\widehat{R\&D}^C$	4,862	1.862	4.218	0	55.6

Table 6: Descriptive statistics on the output additionalities α_i^{TT}, accounting for firm size and age.

Percentages of firms		Firm Size			Firm Age			
N=477		S = 1–49	M = 50 – 249	L = 250-max.	<15	16-30	31-75	76-max.
$\alpha_i^{TT} < 0$	43.40	15.94	51.69	32.37	6.28	10.63	41.55	41.55
$\alpha_i^{TT} = 0$	9.01	23.26	34.88	41.86	9.30	23.26	27.91	39.53
$\alpha_i^{TT} > 0$	46.54	29.52	43.17	27.31	4.85	22.91	39.65	32.60
$\alpha_i^{TT} > 50$	1.05	40.00	-	60.00	-	20.00	60.00	20.00

Note: It should be noted that the number of subsidized firms corresponds to the number of subsidized firms of the Tobit models, where we lose some observations because of missing values in the outcome variables.

Table 7 displays the results of the heteroscedasticity-robust Tobit models on innovation outcome. Models one to five relate to the impact of both types of R&D investment on radical innovation, while models six to ten relate to incremental innovation. The various models per category take into account different collaboration patterns.

Our baseline model for the impact on radical innovation (Model I), shows that both, policy-induced as well as privately invested R&D are positive and highly significant. Furthermore, we see that the coefficients are of a similar size. Put differently, a 10% increase in the counterfactual R&D investment would lead to a 4,4 percentage point increase in the estimated latent dependent variable, i.e. the estimated sales share in radical innovation sales, on average, while a 10% increase in policy induced R&D investment would lead to a 3,7 percentage point increase in the estimated latent variable. Models two and three, containing a dummy for overall collaboration (Model II) and three dummies for vertical, horizontal and collaboration with science (Model III) respectively, show that neither overall, nor a specific type of collaboration displays a significant effect on the estimated sales share in radical innovation. Policy-induced as well as privately motivated R&D investments stay positive and of the same magnitude.

Next, to assess whether these effects change in light of the receipt of a subsidy, we interact privately as well as publicly induced R&D investment with different collaboration patterns. Model IV starts by interacting the overall collaboration dummy with both types of R&D investment. We see that neither one of the interaction terms is significant. In other words, the R&D investments driven by collaboration do not impact the estimated sales share of radical innovation. The same conclusion can be drawn for Model V, where we interact the three different types of collaboration with both types of R&D investment. We can thus conclude that collaborating, with science or another partner, does not improve the policy impact of the subsidy in terms of radical innovation sales.

Turning to the impact on incremental innovation, we see that in line with our expectations, privately motivated R&D expenditures are significant. What strives our attention is the non-significant result of the publicly induced R&D investment, α_i^{TT} (Model VI). While the coefficient is larger in magnitude than it is for radical innovation, it is not statistically significant. Even though the funding agency also supports incremental innovation projects, this finding points to the fact that the publicly induced part of the R&D investment mainly impacts radical innovation.

Going forward, we control for overall collaboration (Model VII) before differentiating between the types of external collaboration partners, namely horizontal, vertical and diagonal collaboration (Model VIII). As was the case for the radical innovation sales share, neither one of the collaboration dummies is significant, nor do they impact the results from the baseline model. When interacting both types of R&D investment with the collaboration dummy, we see that while the counterfactual R&D spending stays significant and positive, both privately and publicly invested parts of the investment that are interacted with collaboration are insignificant.

Finally, in Model X we interact both types of R&D investment with the three different collaboration types. While collaboration with science overall displays a positive and significant impact in this case (as well as the counterfactual R&D spending), we see that parts of these positive impacts turn negative when driven by collaboration (CO_SCIE*$\widehat{R\&D}^{C}$). Furthermore, when publicly induced R&D investment is driven by horizontal collaboration, the insignificant impacts of these variables turns negative and significant if interacted (CO_HOR*α_i^{TT}).

While the results of our models containing collaboration information may seem surprising, there may be several reasons able to explain such findings. For radical innovation, neither one of the collaboration installations have any impact on sales success, even though the funding agency encourages R&D collaboration between firms and especially between firms and science. One explanation for the insignificant results may be the fact that Switzerland is a relatively closed country, where firms are not used to collaborate (as a matter of illustration, roughly 13% of the firms in Switzerland collaborate, compared to some 30% in Belgium for instance). Hence, firms may have developed the necessary skills and know-how over the years and are therefore less dependent on pooling resources with external partners. In this case, collaboration costs may indeed exceed gains in certain settings. In the case of Model X the fact that collaboration with science is negative may be explained by the fact that typically, collaboration with science is needed when firms intend undertaking path-breaking innovations, pushing the technological frontier. For incremental innovation, such type of collaboration is therefore not necessarily attractive, and may deviate resources from where they could have been invested more appropriately in terms of incremental change to existing products. Hence, if the strategy of the firm is to ensure long-term survival perspectives through incremental innovation, it seems that collaborating with science is not maximizing its partnership behavior. The negative impact of collaboration with competitors (horizontal collaboration) and its impact on the sales share of incremental innovation can be explained by the fact that incremental innovations are often times easier to imitate than radical innovations. Teaming up with a competitor may therefore mean losing parts of the market to that partner.

In terms of policy effects in light of collaboration type, our results thus do not show any evidence that subsidized collaborating firms are more productive in terms of new products than non-subsidized firms. To the contrary, we even find weak, yet negative results for the interaction of policy driven investment and horizontal and science collaboration. While the overall policy effect of the Swiss funding agency is positive, the encouragement of collaboration should be revisited.

Before concluding, it should be noted that we took the potential endogeneity of our collaboration variables into account. In Appendix 2.8.3, we estimate a structural equation as introduced by Smith and Blundell (1986) to see if our results are driven by endogeneity. As shown by the results in Table 11 in Appendix 2.8.3, our findings are not driven by endogeneity. Furthermore, we allowed for a longer time lag as one may argue that the impact of both types of R&D investment or collaboration may need more time to impact radical than incremental innovations. As can be seen by Table 12 in Appendix 2.8.4, our conclusions remain unchanged if we allow for a longer time lag. Finally, we also re-estimated the main models controlling for other innovation expenditures. Indeed, one may argue that the way R&D translates into marketable products also depends on the expenditures done on top of R&D investment, independent of whether R&D was subsidized or not.[11] We therefore control for innovation expenditures in the regressions of Table 13 in Appendix 2.8.5, to see if our

[11] We thank an anonymous referee for pointing this out.

findings hold for a given level of innovation investment.[12] As can be seen from Table 13, our conclusions remain unchanged.

It should be noted that due to the lower number of observations in the estimations with an additional time lag and in the estimations including other innovation investment, the significance levels drop slightly, as the lower number of observations induces larger standard errors.[13]

[12] Innovation expenditures include R&D expenditures, but also other expenditures needed in the innovation process, such as expenditures for construction and design, further follow-up investments, including acquisition of other external knowledge, acquisition of specific machinery or software needed for the development or finalization of technologies, as well as expenditures related to the certification of products or packaging technology. Innovation investment enters the equation net of R&D expenditures to avoid double counting.

[13] The missing observations in the models with additional time lags are due to the unbalanced nature of our panel. The missing values in the estimation containing net innovation investment is due the missing values in this variable.

Table 7: Heteroscedasticity-robust Tobit estimates on radical and incremental innovation performance.

	RADICAL					*INCREMENTAL*				
Variables	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
α_i^{TT}	0.371**	0.370**	0.366**	0.203	0.237	0.522	0.521	0.526	0.214	0.289
	(0.153)	(0.154)	(0.153)	(0.377)	(0.356)	(0.349)	(0.352)	(0.361)	(0.395)	(0.383)
$\widehat{R\&D}^C$	0.444***	0.437***	0.428***	0.512***	0.548***	0.364**	0.352**	0.332**	0.782***	0.770***
	(0.119)	(0.117)	(0.121)	(0.158)	(0.158)	(0.148)	(0.144)	(0.146)	(0.235)	(0.207)
RDCOOP		0.416		0.540			0.735		2.126**	
		(0.909)		(0.927)			(1.029)		(0.979)	
FIRMAGE	-0.064***	-0.064***	-0.064***	-0.064***	-0.063***	-0.120**	-0.121***	-0.121***	-0.120***	-0.118***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.047)	(0.047)	(0.047)	(0.046)	(0.045)
FIRMAGE2	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	0.889	0.884	0.934	0.936	1.018	-0.924	-0.930	-0.739	-0.940	-0.627
	(0.917)	(0.919)	(0.916)	(0.945)	(0.969)	(1.172)	(1.171)	(1.147)	(1.170)	(1.121)
LNFIRMSIZE2	-0.095	-0.096	-0.104	-0.101	-0.111	0.117	0.114	0.087	0.116	0.081
	(0.091)	(0.091)	(0.092)	(0.094)	(0.098)	(0.115)	(0.115)	(0.111)	(0.115)	(0.108)
EXPORT	0.053***	0.053***	0.052***	0.052***	0.052***	0.043***	0.042***	0.044***	0.040***	0.043***
	(0.015)	(0.016)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.012)	(0.014)	(0.012)
TECHPOT	1.399***	1.373***	1.336***	1.356***	1.276**	2.151***	2.109***	2.006***	2.021***	1.838***
	(0.436)	(0.422)	(0.456)	(0.434)	(0.501)	(0.389)	(0.381)	(0.390)	(0.394)	(0.429)

continued

continued	*RADICAL*					*INCREMENTAL*				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
CO_VERT			-0.542		-1.534			0.329		-1.172
			(1.763)		(1.874)			(1.157)		(1.341)
CO_HOR			0.227		0.074			3.334		4.707
			(1.480)		(2.231)			(3.220)		(3.903)
CO_SCIE			1.392		3.115			0.257		3.396*
			(2.078)		(2.926)			(2.276)		(1.900)
RDCOOP*α_i^{TT}				0.386					0.663	
				(0.673)					(0.638)	
RDCOOP *$\widehat{R\&D}^C$				-0.101					-0.678	
				(0.215)					(0.416)	
CO_VERT*α_i^{TT}					0.322					0.683
					(0.670)					(0.800)
CO_VERT*$\widehat{R\&D}^C$					0.383					0.431
					(0.276)					(0.267)
CO_HOR*α_i^{TT}					0.381					-0.847*
					(0.489)					(0.507)
CO_HOR*$\widehat{R\&D}^C$					0.077					-0.362
					(0.424)					(0.312)
CO_SCIE*α_i^{TT}					-0.073					0.135
					(0.607)					(0.740)
CO_SCIE*$\widehat{R\&D}^C$					-0.644					-1.103***
					(0.434)					(0.406)
No. of observations	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862

Note: Standard deviations in parentheses are clustered at the firm level and bootstrapped with 150 replications. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

2.7 Conclusion

Our study is an extension of previous studies interested in the effects of public R&D polices on input and/or output additionality. We contribute to current knowledge on the effect of such policy by providing evidence as to where the policy impact is highest, radical or incremental innovation. Furthermore, we take specific collaboration patterns into account to see whether these impacts are affected by R&D collaboration as well as the type thereof (i.e. horizontal, vertical or with science).

In terms of input additionality, we find, in line with previous studies, evidence that allows rejecting the null hypothesis of full crowding out. Taking into account the degree of novelty in terms of innovation performance, this analysis fills a gap by providing evidence on the fact that the impact of the Swiss funding agency is higher for radical than for incremental innovation, as there is no significant impact for the latter in terms of policy induced R&D expenditures. In line with our expectations, privately invested R&D expenditures are positive and significant for both types of innovation output.

Given that the Swiss funding policy encourages firms to collaborate in their R&D activities, our work integrates information on firms' collaboration status. Compared to previous studies that only consider whether or not a firm qualifies as collaborator, we additionally account for specific types of collaboration partners. We are thus able to investigate the effects of different collaboration constellations, i.e. horizontal, vertical and collaboration with science in our framework. While the fact of collaborating as such does not impact the sales share of either incremental or radical innovation, we find that when collaboration types are interacted with R&D investment, parts of the investment driven by collaboration (horizontal and science) turns negative in the case of incremental innovation. Hence, the policy effect is not enhanced by a specific collaboration strategy and collaborative R&D should not necessarily constitute a priority for the Swiss funding agency.

Combing strategic management literature on radical vs. incremental innovation and on collaboration impacts with literature on policy evaluation, our study also allows drawing implications from a managerial perspective. From a managerial point of view, the findings are relevant from mainly two angles. In terms of subsidy strategy, it is vital for a manager to know that it is more likely for a subsidy to have the desired impact when used for more radical innovation projects. From a collaboration strategy perspective, it is important to know that there are also downsides to engaging into collaboration. Hence, if tempted to engage in R&D collaborations in order to increase the probability of receiving a subsidy, managers should be aware that there may also be downsides to this strategy, and that the impact of the subsidy may even turn negative in light of collaboration.

Despite all efforts, our analysis is not without limitation. One improvement would be to have access to panel data, allowing following firms over time, thereby being able to analyze the impact of a subsidy in a before-after setting.

Furthermore, having information about the rejected applicants would have allowed for a series of additional robustness checks to strengthen our findings.

2.8 Appendices

2.8.1 Appendix: Additional descriptive statistics

Table 8: Industry distribution.

Industry	Number of firms	Percentages	Percentage of subsidized firms per sector
1 Construction, mining, energy	441	7.25	5.90
2 Consumer goods (food, beverages, tobacco, textiles, clothing)	433	7.12	9.01
3 Intermediate goods (paper, printing, chemicals, pharmaceuticals, rubber, plastics, minerals, basic metals)	1,051	17.27	9.13
4 Investment goods (fabricated metals, machinery & equipment, electrical equipment, electronics and optical products, medical instruments, watches, vehicles, and other manufacturing)	2,111	34.7	13.55
5 Traditional services (trade, transportation, telecommunications)	923	15.17	4.55
6 Knowledge-based services (banking, insurance, information technology & services, technical commercial services)	874	14.37	5.72
7 Other services	251	4.13	2.79
Total	**6,084**	**100**	**8.97 (on average)**

Table 9: Size class distribution.

Size class	Size class distribution	Number of firms	Percentages	Percentage of subsidized firms per size class
1 Small-sized firms	1 – 49	2,489	40.91	5.10
2 Medium-sized	50 – 249	2,405	39.53	10.27
3 Large-sized	250 – max.	1,190	19.56	14.45
	Total	**6,084**	**100**	**8.97 (on average)**

2.8.2 Appendix: Robustness check for the matching estimation accounting for potential selection on unobservables

An essential assumption to conduct a valid matching estimation is the conditional independence assumption (CIA). Indeed, for the matching estimation to be valid, the outcome has to be statistically independent of program participation, conditional on a series of observable characteristics. This fundamental assumption is however not testable. Therefore, we test the robustness of our matching estimation results by taking into account the selection on observables. We do so using an instrumental variables (IV) approach.

To conduct our IV regression, we employ two instruments for the subsidy receipt. First, we use the likelihood of receiving a subsidy by region and industry (IV_1); and second, we use the likelihood of collaborating with science by industry (IV_2).

IV_1 is justified by the fact that funding agencies often have preferences in terms of location or industries. Even though such priorities are not formal conditions, it may very well be that a firm based in direct proximity of a funding agency is more aware of the policy and is more visible to the decision makers than a firm that is situated further away. Hence, being part of a region or an industry where the likelihood of receiving a subsidy is high, is likely to impact the receipt of a subsidy of firm *i*. The rationale of using the industry average of collaboration with science institutions as an instrument (IV_2) documents the fact that some technological trajectories have closer relationships to universities and other research centers. Having a closer relationship to science collaboration increases the likelihood of being retained for funding, given that the Swiss government aims at increasing industry – science links.

Both instruments fulfill the statistical tests for being valid instruments. In the first stage, both IVs are highly significant. In the second stage, the Hansen J-test of overidentification is insignificant. Hence, both from a statistical as well as from an economic point of view, our instruments are valid. As displayed in Table 10, the results of the IV estimation are in line with what we find in our matching estimation.

Table 10: Robustness test with instrumental variables for subsidies on R&D intensity.

	First stage Probit:	Second stage Tobit:	
Variables	RDCOOP	RADICAL	INCREMENTAL
IND_COOP (IV_1)	-0.560*		
	(0.307)		
COOP_EXP (IV_2)	1.146***		
	(0.047)		
RDINT	0.011	0.446***	0.387***
	(0.007)	(0.068)	(0.081)
FIRMAGE	-0.001	-0.061***	-0.080***
	(0.001)	(0.014)	(0.017)
FIRMAGE2	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	0.01	0.865	-1.235
	(0.072)	(1.083)	(1.269)
LNFIRMSIZE2	-0.003	-0.08	0.124
	(0.007)	(0.109)	(0.129)
EXPORT	0.001	0.031***	0.043***
	(0.001)	(0.011)	(0.012)
TECHPOT	0.096***	1.652***	2.278***
	(0.027)	(0.310)	(0.361)
RDCOOP		1.283	0.12
		(1.210)	(1.398)
1ST STAGE RESIDUALS		-0.026	0.248
		(0.172)	(0.198)
No. of observations	4,224	4,224	4,224

Note: IV_1 represents the industry mean of collaborating firms in previous years. IV_2 reflects the firm's overall collaboration experience. The second stage Tobit models employ heteroscedastic-robust estimations. All stages include an intercept, time and industry dummies (not presented). Standard errors (in parentheses) are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%).

2.8.3 Appendix: Robustness check for potential endogeneity of the collaboration variable in the innovation outcome equation

In our innovation outcome estimations, we face the problem that one of our main explanatory variable might be endogenous, namely our collaboration variables. In order to test if our results are affected by potential endogeneity, we conduct a structural equation approach introduced by Smith and Blundell (1986). For the sake of this robustness check, we defined two instrumental variables for our potential endogenous collaboration variable *RDCOOP* following the advices of Murray (2006). Our first instrumental variable *IND_COOP* (IV_1) captures the share of collaborating firms by industry (at nace-2-level) in previous years. The rationale behind this instrument is that the higher the share of collaborating firms in a given industry, the higher is the probability that a firm *i* in industry *j* engages in collaboration in a given period. Our second instrumental variable *COOP_EXP* (IV_2) is defined as the overall collaboration experience of a firm *i* in our sample, and takes values from 0 to 5. The more experience a firm has in collaboration, the higher the likelihood of this firm to engage in collaboration again.

To further test the statistical validity of our instruments employed for the Blundell-Smith test of exogeneity, we ran a couple of tests on the validity of the chosen instruments. It should be noted though that we have to use the standard Two Stage Least Squares (2SLS) approach, as standard tests of over-identification do not exist for the Blundell-Smith approach. Our two excluded instruments are jointly statistical significant at the 1%-level ($F(2, 2722) = 647.97$), and the Hansen

J test of over-identification cannot be rejected for radical innovation performance (Hansen J statistic = 2.540, p=.111), nor for incremental innovation performance (Hansen J statistic = 2.578, p=.108). Finally, both our instruments are statistically significant in the first stage of the equation. Considering the above results, we can conclude that our two instrumental variables satisfy the statistical requirements.

As can be see seen in Table 11, the first stage residuals are not significant in the innovation outcome equations. Therefore, we can conclude that our findings are not driven by endogeneity.

Table 11: Robustness test with instrumental variables for R&D collaboration on innovation outcome.

	First stage Probit:	Second stage Tobit:	
Variables	RDCOOP	RADICAL	INCREMENTAL
IND_COOP (IV_1)	-0.560*		
	(0.307)		
COOP_EXP (IV_2)	1.146***		
	(0.047)		
RDINT	0.011	0.446***	0.387***
	(0.007)	(0.068)	(0.081)
FIRMAGE	-0.001	-0.061***	-0.080***
	(0.001)	(0.014)	(0.017)
FIRMAGE2	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	0.01	0.865	-1.235
	(0.072)	(1.083)	(1.269)
LNFIRMSIZE2	-0.003	-0.08	0.124
	(0.007)	(0.109)	(0.129)
EXPORT	0.001	0.031***	0.043***
	(0.001)	(0.011)	(0.012)
TECHPOT	0.096***	1.652***	2.278***
	(0.027)	(0.310)	(0.361)
RDCOOP		1.283	0.12
		(1.210)	(1.398)
1^{ST} STAGE RESIDUALS		-0.026	0.248
		(0.172)	(0.198)
No. of observations	4,224	4,224	4,224

Note: IV_1 represents the industry mean of collaborating firms in previous years. IV_2 reflects the firm’s overall collaboration experience. The second stage Tobit models employ heteroscedastic-robust estimations. All stages include an intercept, time and industry dummies (not presented). Standard errors (in parentheses) are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%).

2.8.4 Appendix: Using a different time structure

Table 12: Robustness check controlling for additional time lags (including a survey-time-lag, corresponding to a 4-year-time-lag). Heteroscedasticity-robust Tobit estimates on radical and incremental innovation performance.

	RADICAL					*INCREMENTAL*				
Lagged variables	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
α_i^{TT}	0.809*	0.802*	0.808*	0.837	0.844	0.114	0.106	0.113	0.031	0.034
	(0.441)	(0.451)	(0.449)	(0.631)	(0.570)	(0.466)	(0.460)	(0.464)	(0.837)	(0.743)
$\widehat{R\&D}^C$	0.844***	0.811***	0.835***	0.809***	0.813***	0.875***	0.859***	0.863***	0.874***	0.873***
	(0.165)	(0.164)	(0.169)	(0.279)	(0.307)	(0.215)	(0.227)	(0.222)	(0.318)	(0.311)
RDCOOP		4.238***		4.411***			1.800		1.664	
		(1.399)		(1.214)			(1.899)		(2.397)	
FIRMAGE	-0.017	-0.017	-0.017	-0.018	-0.018	-0.026	-0.027	-0.025	-0.026	-0.025
	(0.039)	(0.040)	(0.039)	(0.040)	(0.039)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)
FIRMAGE2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	4.045**	4.214**	4.408***	4.110**	4.165***	-0.259	-0.172	-0.125	-0.005	0.036
	(1.787)	(1.725)	(1.693)	(1.674)	(1.618)	(2.292)	(2.268)	(2.307)	(2.254)	(2.244)
LNFIRMSIZE2	-0.155	-0.193	-0.214	-0.185	-0.192	0.249	0.233	0.224	0.219	0.213
	(0.200)	(0.187)	(0.180)	(0.179)	(0.168)	(0.243)	(0.242)	(0.243)	(0.240)	(0.235)
EXPORT	0.042**	0.033	0.038*	0.034	0.038*	0.079***	0.075***	0.077***	0.074***	0.075***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.020)	(0.024)	(0.022)	(0.023)	(0.022)	(0.023)
TECHPOT	1.437***	1.255**	1.214**	1.250**	1.205**	1.922***	1.856***	1.835***	1.858***	1.810***
	(0.492)	(0.496)	(0.490)	(0.499)	(0.508)	(0.553)	(0.538)	(0.539)	(0.538)	(0.536)

continued

continued	*RADICAL*					*INCREMENTAL*				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
CO_VERT			2.193		0.752			2.451		1.947
			(1.628)		(1.955)			(2.788)		(3.730)
CO_HOR			5.955**		5.449			2.208		1.543
			(2.961)		(3.967)			(2.220)		(2.785)
CO_SCIE			-0.666		1.313			-1.448		-0.851
			(2.032)		(3.006)			(2.389)		(2.914)
RDCOOP* α_i^{TT}				-0.242					0.420	
				(0.671)					(0.865)	
RDCOOP * $\widehat{R\&D}^C$				-0.033					0.004	
				(0.436)					(0.459)	
CO_VERT* α_i^{TT}					0.410					0.381
					(1.094)					(1.217)
CO_VERT* $\widehat{R\&D}^C$					0.556					0.271
					(0.445)					(0.670)
CO_HOR* α_i^{TT}					0.575					-0.249
					(0.753)					(1.010)
CO_HOR* $\widehat{R\&D}^C$					0.173					0.262
					(0.515)					(0.539)
CO_SCIE* α_i^{TT}					-0.780					0.312
					(1.097)					(1.347)
CO_SCIE* $\widehat{R\&D}^C$					-0.643					-0.326
					(0.704)					(0.594)
No. of observations	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924

Note: Standard deviations in parentheses are clustered at the firm level and bootstrapped with 150 replications. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

2.8.5 Appendix: Accounting for other innovation investments

Table 13: Robustness check: Heteroscedastic-robust Tobit estimates on radical and incremental innovation performance, holding other innovation investments constant.

	RADICAL			*INCREMENTAL*		
Variables	Model I	Model II	Model III	Model VI	Model VII	Model VIII
α_i^{TT}	0.416*	0.417*	0.418*	0.598	0.599	0.603
	(0.250)	(0.254)	(0.251)	(0.381)	(0.386)	(0.397)
$\widehat{R\&D}^{C}$	0.528***	0.518***	0.539***	0.749***	0.715***	0.689***
	(0.147)	(0.152)	(0.155)	(0.244)	(0.235)	(0.232)
INNO_INV	0.303***	0.303***	0.301***	-0.282	-0.281	-0.283
	(0.091)	(0.091)	(0.092)	(0.257)	(0.255)	(0.257)
RDCOOP		0.464			1.750*	
		(1.206)			(1.054)	
CO_VERT			2.136*			-0.085
			(1.267)			(1.618)
CO_HOR			-2.046			2.384
			(2.824)			(2.247)
CO_SCIE			-1.994			2.669
			(1.623)			(1.647)
FIRMAGE	-0.127**	-0.127**	-0.129**	-0.097***	-0.098***	-0.095***
	(0.054)	(0.055)	(0.056)	(0.031)	(0.032)	(0.031)
FIRMAGE2	0.000*	0.000*	0.000*	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	1.446	1.438	1.352	3.604	3.592	3.657
	(1.198)	(1.189)	(1.169)	(2.318)	(2.287)	(2.257)
LNFIRMSIZE2	-0.122	-0.123	-0.110	-0.310	-0.314	-0.329
	(0.115)	(0.113)	(0.111)	(0.217)	(0.214)	(0.211)
EXPORT	0.054**	0.053**	0.053**	0.019	0.016	0.015
	(0.023)	(0.024)	(0.023)	(0.019)	(0.020)	(0.019)
TECHPOT	1.257**	1.235**	1.320***	2.255***	2.172***	2.060***
	(0.527)	(0.498)	(0.462)	(0.459)	(0.454)	(0.443)
No. of observations	3,477	3,477	3,477	3,477	3,477	3,477

Note: Bootstrapped standard deviations in parentheses are clustered at the firm level. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

CHAPTER 3

Cooperating with external partners: The importance of diversity for innovation performance

A version of this chapter has been published in European J. International Management, reproduced by permission from Inderscience Publishers:

Beck, M. and Schenker-Wicki, A. (2014) ‘Cooperating with external partners: the importance of diversity for innovation performance’, European J. International Management, Vol. 8, No. 5, pp.548–569.

Abstract: This paper investigates how diversity in R&D cooperation networks affects firms' innovation performance output as measured by each firm’s sales share of innovative products. To address this question, the authors analyze a large-scale sample of microdata on Swiss firms from five waves (1999, 2002, 2005, 2008 and 2011) of the Swiss innovation survey using panel data analysis. The findings suggest that firms with greater diversity in their cooperation network benefit by generating new product innovations, and that the diversity benefit is greatest for small firms. The study further detects a curvilinear relationship between diversity of collaborator types and innovation performance, and emphasizes the importance of appropriate HRM and knowledge management policies and practices in providing firms with an effective mechanism for maximizing the benefits from diversified cooperation networks.

Keywords: Collaboration for innovation; cooperation; strategic alliances; diversity; innovation performance; human resource management policies and practices; knowledge management; absorptive capacity; small firms.

3.1 Introduction

This paper focuses on firms' openness in cooperation networks with external partners and analyzes how diversity in types of collaboration partners influences firms' innovation performance. In highly industrialized countries, firms need to be innovative to compete in their markets. For many enterprises, the generation and successful market introduction of new innovative products are crucially important for securing future business. However, becoming and remaining innovative are difficult, especially in technological and market environments characterized by high knowledge intensity and uncertainty (Teece, 1986). Sources of knowledge and competences—necessary for creating new products and processes—are dispersed widely and difficult to locate. Additionally, since the 1980s, globalization has led to a more competitive and dynamic environment while product and technology life cycles have become shorter. Both effects have challenged firms to redefine their innovation search strategies and widen their technological bases (Katila & Ahuja, 2002).

Given these circumstances, firms need to develop new knowledge-appropriating architectures or, as Teece (1992, p. 22) argues, "successful technological innovation requires complex forms of business organization." Contrary to the Schumpeter's lonely entrepreneur, today's firms' innovations are rarely generated in isolation. Instead, innovating firms have begun to search for partners, and increasingly build their innovation activities on external knowledge sources, that complement their own capabilities (Al-Laham, Amburgey, & Baden-

Fuller, 2010; Colombo, Laursen, Magnusson, & Rossi-Lamastra, 2011; Grimpe & Kaiser, 2010; Henttonen & Ritala, 2013; Katila, 2002). Thus, firms interact with their external environment to gain access and to acquire new ideas for future innovations (Caloghirou et al., 2003).

In this context, cooperation and other means of collaboration among partners provide firms with an attractive means of organizing innovative activities (Doz, Santos, & Williamson, 2001). This study takes a resource-based approach (Penrose, 1959; Tsang, 2000) and contributes to the discussions on how diversity of partner types in collaborative networks influences firm innovation performance and how this relationship is affected by firm size and internal absorptive capacity.

The construct of innovation performance can be linked to Schumpeter's classification of innovation as the successful introduction of new products, new production processes, new means and sources of supply, new exploitation of markets, and new ways to organize business (Schumpeter, 1912). This study focuses on innovation output and considers only product innovations, measured here by the sale shares of new or significantly improved products in total turnover.

In our empirical work, we refer to cooperation activities as formal agreements with external partners such as other firms, suppliers, customers or research institutions on joint research and development (R&D) activities. Collaboration can facilitate access to complementary assets, create opportunities to exploit synergies (Becker & Dietz, 2004; Bercovitz & Feldman, 2007; Dachs, Ebersberger, & Pyka, 2008), and initiate intensive learning processes (Soo, Devinney, & Midgley, 2007).

Some scholars argue that, with the establishment of cooperation activities in the innovation process, the firms' perspective for generating innovations has changed from an internal and isolationist type to a more open model of innovation, that includes inter-firm R&D collaborations (Chesbrough, 2003a; Chesbrough, Vanhaverbeke, & West, 2006; Huizingh, 2011; Lichtenthaler, 2008), mass customization and personalization (Tseng & Piller, 2003), and external sourcing of knowledge (Laursen & Salter, 2006).

Various empirical studies have addressed the effects of different open search strategies for firms' innovation outcomes (Henttonen, Ritala, & Jauhiainen, 2011; Katila & Ahuja, 2002; Sofka & Grimpe, 2010). Most of these studies (e.g., Chiang & Hung, 2010; Leiponen & Helfat, 2010) build on the concept of *external search depth* and *external search breadth*, initiated by Laursen & Saulter (2006), who differentiate between the intensity of the use of external knowledge sources (*depth*) and the number of external sources used (*breath*). The results of these studies indicate that the use of both search strategies—specialized (depth) and more inclusive (breath)—are important factors for innovation outcomes. However, there is still a lack of understanding about the specific effects of different search strategies for innovation performance. More precisely, little is known about the effects of focused versus diversified cooperation strategies and about the potential implications of an over-diversified cooperation strategy in a firm's external partner network. In this area, more empirical studies are needed to determine the practical implications for firms and policy makers in the formulation of appropriate technology policies.

More insight into this relationship would also allow initiating appropriate knowledge management and human resource management (HRM) policies and practices. Management scholars have already recognized the relevance of HRM and knowledge management for fostering innovation activities and creating an innovative culture inside the firm (Cabello-Medina, Lopez-Cabrales, & Valle-Cabrera, 2011; Jimenez-Jimenez & Sanz-Valle, 2005; Laursen & Foss, 2003; Nonaka & Takeuchi, 1995; Schuler & Jackson, 1987; Wozniak, 1987). In this regard, HRM has launched various initiatives in the areas of (global) talent management, compensation and reward management, recruitment and selection, job design and work arrangements, performance management, and training and development; and it has further worked to build competences in corporate leadership (Aguirre, Post, & Hewlett, 2009; Kesting, Mueller, Jorgensen, & Ulhoi, 2011; Schuler & Jackson, 2007). These HRM approaches have mainly focused on promoting and facilitating innovation activities within firms. Less attention has been paid to how HRM and knowledge management can contribute to better integration of external knowledge, capabilities, and technology located outside the firm, or better management of the firm's external cooperation network. This is especially valid in the early stages of innovation— including idea creation and idea conversion—with partners outside the firm (Jaruzelski, Loehr, & Holman, 2012).

In order to gather more empirical evidence for the aforementioned open questions, this work extends the existing literature by conceptualizing the relationship between the diversity of cooperation partner types in collaborative networks and firm innovation output performance. The goal of this work is to examine the potential for the decreasing returns of an over-diversified cooperation network, taking into account firm size and internal absorptive capacity. To the best of our knowledge, this is the first empirical study using a large-scale representative panel data structure with cross-sectional firm-level data from manufacturing and service industries, which identifies a curvilinear relationship between cooperation partner type diversity and firm innovation performance. The analysis uses data from five waves (1999, 2002, 2005, 2008 and 2011) of the Swiss innovation survey and employs a Tobit panel data regression method.

The paper is structured into five sections as follows. The next section introduces key underlying theoretical arguments, presents previous literature, and formulates the main hypotheses for empirical analysis. Section three presents the data and the methodological approach. Results are discussed in section four. Finally, section five concludes and gives an outlook for future research.

3.2 Overview of the theoretical background and previous studies

In the following section, the relationship between cooperation activities in the innovation process and subsequent firm innovation performance is elaborated from a theoretical and empirical perspective.

3.2.1 Key theoretical arguments

From a theoretical perspective, three main streams of literature deal with the effect of inter-firm collaboration on the innovation process. The first branch of literature falls into the “neoclassical” field of mainstream industrial organization (D'Aspremont & Jacquemin, 1988; Dasgupta & Stiglitz, 1980; Martin, 1994; Martin, 2002; Spence, 1984) and transaction cost economics (Jaffe, 1996; Williamson, 1975, 1985). The second stream incorporates strategic management approaches to inter-firm arrangements (Coombs, 1996; Hagedoorn, 2002; Nooteboom, 1999). Here, the emphasis is on improving the firm’s competitive position (Hagedoorn, 1993; Porter, 1980, 1990), exploration of complementary external resources and capabilities (Richardson, 1972; Teece, 1982, 1986, 1992), and creation and acquisition of new knowledge and technology (Dodgson, 1991; Granstrand, Oskarsson, Sjoberg, & Sjolander, 1990; Pavitt, 1988).[14] As reported by management literature (Hagedoorn, Link, & Vonortas, 2000; Rosenfeld, 1996), large multinational companies as well as small- and medium-sized firms have

[14] Caloghirou et al. (2003) provide a detailed overview of theoretical perspectives regarding transaction cost economics, industrial organization, and (strategic) management literature.

built up more and closer relationships with other companies since the mid-1990s. These formal or informal joint activities enable firms to gain market access, avoid duplicative research and benefit from synergies due to learning and economies of scale and scope (van de Vrande, de Jong, Vanhaverbeke, & de Rochemont, 2009; Zeng, Xie, & Tam, 2010).

According to transaction cost theorists, cooperation can be seen as an efficient hybrid coordination mechanism between markets and internal organization that reduces transaction costs. While markets—and therefore prices—are expected to allocate resources in an efficient way to generate optimal outcomes, there are considerable doubts that prices are adequate signals in a technological environment characterized by high uncertainty (Teece, 1992). Williamson (1975) argues that market imperfections arise not only from the difficulty of finding relevant information on prices and quality (Coase, 1937), but also from the difficulty of managing economic activities with incomplete contracts. Full integration also has its weaknesses: one example is the provision of appropriate incentives and compensation. Full integration of R&D can also narrow the view of workers on changes in technology (Dosi, 1997). Therefore, from a transaction cost perspective, cooperation may reduce transaction costs through improved flexibility and rapid adjustment to industrial changes and demand (Das, Sen, & Sengupta, 1998).

Another perspective on firms' decisions whether or not to cooperate is the trade-off between incoming and outgoing flows of knowledge. A firm should aim to maximize incoming spillovers while minimizing outgoing spillovers. Firms with more effective and efficient R&D, have what is known as higher internal capacity of the firm (Cassiman & Veugelers, 2002), and are more able to take advantage of external sources of knowledge. This is related to the concept of "absorptive capacity" established by Cohen & Levinthal (1989, 1990), who argue that such capacity is crucial for benefitting from externally generated knowledge.

The third main stream—evolutionary economics—emphasizes the importance of openness in the innovative opportunity search strategy of the firm. Through its access to external technological sources, a firm is able to choose among a greater variety of technological opportunities (Metcalfe, 1994). This provides the firm with the possibility of creating or combining new technologies and knowledge, thereby increasing the probability it will become a successful innovator (Levinthal & March, 1993; Nelson & Winter, 1982). However, it may be difficult to combine many types of knowledge, and the possibility of gaining benefits from external sources is related to industry technology characteristics, particularly inherent technological opportunities (Klevorick, Levin, Nelson, & Winter, 1995).

3.2.2 Cooperation and innovative activities

When considering the increasing importance of cooperative activities in the innovation process (Hippel, 1988), most previous studies focus on determinants and motives for cooperative behavior with different partners (Fritsch & Lukas, 2001; Kaiser, 2002; Miotti & Sachwald, 2003; Tether, 2002). As a result, the effect of cooperative behavior on the input and output of innovation performance (Belderbos et al., 2004a) still remains under-examined and requires further research (Lichtenthaler, 2011). Firms engaged in formal collaborative research generally have higher R&D expenditures (Becker & Dietz, 2004) and higher R&D profits (Belderbos et al., 2004a). With respect to innovation input performance, collaborating firms seek to increase resources and capabilities by combining their resources and utilizing complementarities (Gulati, 1995; Kogut, 1988).

3.2.3 Types of cooperation partners and innovation performance

The choice to cooperate with a certain type of partner is a trade-off of expected gains against expected risks (Katila et al., 2008; Powell, Koput, & Smith-Doerr, 1996). Different types of partners have specific characteristics affecting how cooperation is managed (Whitley, 2002).

In recent studies analyzing the relationship between cooperation partner type and innovation performance in terms of increased product or process innovations, no clear-cut results can be found, but some tendencies can be discerned. Cooperation with clients benefits firms in the improvement of product innovations by improving market information (Fritsch & Lukas, 2001) directly involving R&D teams (Atuahene-Gima, 1995). Cooperation with suppliers can reduce lead-time and risks while increasing flexibility, product quality, and market adaptability (Chung & Kim, 2003). Cooperation activities with competitors entails the "hold-up" problem, which means that cooperation is more beneficial for both parties if common problems and/or activities are beyond the competitor's sphere of influence (Ritala & Hurmelinna-Laukkanen, 2009; Tether, 2002).[15] Cooperation with research organizations provides access to scientific and technological knowledge (Drejer & Jorgensen, 2005; Lundvall, 1992), and plays an important role in both technological innovations (Bozeman, 2000; Vuola & Hameri, 2006) and the opening of new markets (Belderbos et al., 2004a).

Diversity of cooperation partners affects firms' innovation activities. Evolutionary economists point out that a wide range of external partners and sources is crucial for increasing the variety of knowledge within the firm (Nelson & Winter, 1982). Further, such variety generates opportunities to innovate through the creation of new knowledge and technology combinations (Chesbrough, 2003b; Laursen & Salter, 2006). Laursen & Salter (2006) argue that different strategies for using different search channels— suppliers, users, other firms, universities, and other research institutions—are important in explaining heterogeneity in innovation performance. Other studies find empirical evidence that the inclusion of diverse partners increases the probability of achieving product innovations (Becker & Dietz, 2004) and increases the novelty of those innovations (Nieto & Santamaria, 2007).

[15] Cooperative activities in basic research or establishing new standards are potential areas of common interest (Amara & Landry, 2005; Gemünden, Heydebreck, & Herden, 1992), as are activities in the presence of a regulatory change (Tether, 2002).

Broadly, greater variety in information inputs of all types benefits the innovative ability of the firm. According to evolutionary economists, firms should not persist in a specific knowledge trajectory because the benefits decline over time (Dosi, 1988). Hence, the firm should rely on different paths to accumulate new ideas for innovative activities (Nelson & Winter, 1982). Other scholars argue that implementing a diversified cooperating network improves the firm's capacity for organizational learning, its ability to adapt to changes in demand and technology, and generally contributes to problem solving and innovation (Levinthal & March, 1993; March, 1991). Indeed, recent empirical studies have provided some evidence that a broad search strategy for new knowledge and innovative ideas can improve firms' ability to innovate (Henttonen & Ritala, 2013; Laursen & Salter, 2006; Sofka & Grimpe, 2010).

These reflections and findings are in alignment with our expectation that diversity in cooperation partner types within its collaborative network can increase the firm's innovation output.

Our first hypothesis can be formulated as follows:

Hypothesis 3.1: The more diverse a firm's cooperation arrangements with external partners are, the higher its innovation output performance will be.

3.2.4 Impact of diversity in cooperation partners and innovation performance

The benefits of joint innovative activities increase as the external partner's resources and capabilities better complement the firm's own available resources.

However, these benefits must be weighted against transactions costs (Pisano, 1990; Williamson, 1989). These costs are incurred in the coordination, management, and control of all partners (Knudsen & Mortensen, 2011; Nieto & Santamaria, 2007). Specificity of assets, asymmetric information, opportunistic behavior, and uncertainty about the appropriability of expected innovation returns also factor into the costs of cooperation. The integration of diverse partners creates better exploitation of complementary resources and capabilities, but this relationship may be affected by mounting transaction costs. We take the above-mentioned costs into consideration in our analysis of the relationship between diversity in cooperation partner types and innovation performance.

We also account for each partner type as a separate search and learning space embedded in an environment with different routines, habits, norms, and rules (Brown & Duguid, 2002; Cook & Brown, 1999b). Despite the possibility that establishing new linkages to diverse partners can generate substantial innovation advantages for the firm, there is the inherent risk of increased opportunistic behavior. In that regard, relying on limited types of partners can facilitate innovative activities by establishing routines (Levinthal & March, 1981) and forming reliable and trustworthy ties between cooperation partners. Different knowledge domains require different organizational practices to manage knowledge search effectively and efficiently, and this may be especially challenging if multiple types of partners are involved. In addition, managing relationships to external partners requires managerial attention, which is not an unlimited resource (Ocasio, 1997). In a nutshell, we expect that diversity in cooperation partners might be advisable for a firm, but that the integration of too many different types of cooperation partners could be negatively related to innovation performance because of its high complexity.

Hypothesis 3.2: The relationship between diversity in types of cooperation partners and innovation output performance follows an inverted U-shaped curvilinear form.

3.2.5 Diversity in cooperation partners as moderated by internal absorptive capacity and firm size

In order to gather more insights about potential appropriability mechanisms, we proceed by analyzing some key moderating effects in the relationship between diversity in cooperation partners and innovation performance (see e.g., Ahuja, Lampert, & Novell, 2013), starting with the moderating role of internal absorptive capacity. The concept of absorptive capacity (Cohen & Levinthal, 1990) emphasizes that firms' in-house R&D activities provide them with the necessary know-how to absorb and apply external knowledge and create product innovations. Recent research has focused on the moderating effect of firms' R&D efforts on innovation performance (Grimpe & Kaiser, 2010). Previous research (Grimpe & Kaiser, 2010; Mowery et al., 1996) has also found positive effects of firms' R&D investments on their ability to take advantage of external knowledge sources. Grimpe & Kaiser (2010) argue that firm-specific (internal) R&D expenditures enhance the firm's ability to improve its "integrative capabilities," which improves exploitation of resource and technology combinations derived from both internal and external sources. Thus, conducting high levels of (internal) R&D activities prevents the loss of valuable process knowledge in manufacturing and engineering, while helping the firm fully exploit external knowledge (Kotabe, 1990; Weigelt, 2009). In this way, R&D investment is considered a justifiable proxy for internal absorptive capacity. We assume that higher levels of R&D expenditures positively moderate the relationship between diversity in types of cooperation partners and innovation performance.

> *Hypothesis 3.3: The relationship between diversity in cooperation partner types and innovation output performance is positively moderated by higher levels of R&D expenditures such that maximum innovation performance can be achieved with more diverse cooperation partners.*

The literature has shown that firm size plays a characteristic role in innovation activities (Cassiman & Veugelers, 2002). As small and medium-sized enterprises (SMEs) are necessarily limited in size and human and financial resources, collaborative innovation provides them with an interesting mode of organizing their innovation activities and gaining access to externally located knowledge sources (Gronum, Verreynne, & Kastelle, 2012; Kesting et al., 2011; Powell et al., 1996; Teirlinck & Spithoven, 2013; van de Vrande et al., 2009). However, organizing external relationships costs resources and managerial attention, and it can be challenging for SMEs to manage a diversified network effectively. Consequently, smaller firms might not see the full potential of their external relationships. Conversely, smaller firms may have a better overall view of their collaboration network than larger firms, and may be better able to place people with the ideal combination of business sense and technological expertise in the right places to reap the full value of cooperative arrangements. We expect that smaller size positively moderates the relationship between diversity in cooperation networks and innovation outputs. We therefore state the following hypothesis:

> *Hypothesis 3.4: The relationship between diversity in cooperation partner types and innovation output performance is positively moderated by small-sized firms, such that maximum innovation performance can be achieved with more diverse cooperation partners.*

3.3 Data and model specification

3.3.1 Data

For the empirical analysis, this study uses micro-aggregated firm-level data from Swiss firms. The data is derived from postal innovation surveys conducted by the Swiss Economic Institute (KOF) in the years 1999, 2002, 2005, 2008, and 2011. In total, the panel contains 11814 observations from 5703 firms. The aim of the survey is to observe and collect data about technological innovation. The questionnaires are methodologically similar to the well-established Community Innovation Survey (CIS) from the European Commission. The dataset is designed as a panel and contains detailed firm-level data on firm characteristics (size, exports, sector affiliation), R&D and innovation activities, cooperation motives, and general activities among other things. The survey provides a representative sample of Swiss firms, including firms from all relevant manufacturing, service, and construction sectors. The survey is based on a disproportionate stratified random sample (according to firm size), capturing firms with at least five employees but with full coverage of the upper part of the distribution. The response rates are 33.8% (1999), 39.6% (2002), 38.7% (2005), 36.1% (2008), and 35.9% (2011). In our study, we focus on R&D active firms; thus we only use data from firms that conducted R&D activities in the relevant period.[16] The final panel for analysis is comprised of 4488 observations from 2649 firms. The average firm participates 1.7 times in the survey, which is satisfactory regarding the relevant time span of the survey.

3.3.2 Model specification

For the purpose of this study, we define diversity in a collaboration network as the number of different types of partners having a formal R&D cooperation arrangement with the focal firm. In our analysis, we define seven different types of cooperation partners: customers and clients, suppliers, competitors, non-competing firms, firms from the same corporate group, universities, and other research institutions. In total, we estimate four different model specifications to

[16] As not all firms in our panel are involved in R&D activities and we do not control for possible selection bias, our results can only be interpreted for firms that conduct R&D. The Heckman procedure is one possibility to detect a possible bias in the sample.

explain innovation performance. In the first, we begin by assessing whether the inclusion of different types of cooperation partners influences innovation performance (model 1). Therefore, we include a collaboration diversity variable (collab_diversity) in our model to count the number of cooperation partner types. Next, we examine the shape of the relationship between diversity in cooperation partners and innovation performance (model 2). To control for an inverted U-shaped curvilinear relationship and potentially decreasing marginal effects of diversity, we include the squared term of the collaboration diversity variable (Grimpe & Kaiser, 2010; Laursen & Salter, 2006).[17]

The final two model specifications test our hypotheses regarding the moderating effects of internal absorptive capacity and firm size on the previously modeled curvilinear relationship. In model 3, we approximate internal absorptive capacity by calculating the ratio of R&D expenditures to total sales, and interact this with the collaboration diversity variable. In model 4, we test the hypothesis on the moderating effect of firm size by interacting collaboration diversity with the dummy variable for small-sized firms. A significant positive coefficient would indicate a moderating effect for the absorptive capacity or firm size variable and would shift the tipping point of the curvilinear form to the right.

[17] An inverted U-shaped relationship would be indicated through a positive significant coefficient of collaboration diversity variable, and a negative significant coefficient of the squared term. Joint significance of both variables would also allow the assumption of an inverted U shape (see for example Grimpe & Kaiser, 2010). A detailed discussion of the statistical test for a U-shaped relationship provide Lind and Mehlum (2010).

A. Dependent variables

The dependent variable is the output innovation performance of firms. Firms' innovation output is measured by the ratio of new or considerably improved product turnover divided by total firm turnover, taking values between 0 and 100. In alignment with the definitions of the Oslo Manual (OECD, 1992), these products have to be new to the firm or modified in a substantial way, excluding products with only minor modifications such as customer specifications and design adjustments. This measure has broad acceptance in empirical analysis and has been used in several previous empirical studies (Belderbos, Carree, & Lokshin, 2004b; Grimpe & Kaiser, 2010; Loof & Heshmati, 2002). In our analysis, we employ its natural logarithm (e.g. Arvanitis & Bolli, 2012).

B. Independent variables

We consider variables that reflect the theoretical and empirical insights explained in the previous section. In our model, we take the resource-based approach to explaining innovation performance. Diversity in collaboration partner types is represented by the variable *collab_diversity* counting the number of the different types of external partners in a firm's cooperation network.

Following the argument that the firm's stock of resources and capabilities is crucially important for its benefiting from cooperation with external partners, our model captures several firm characteristic variables. The amount of resources invested in innovation activities influences the decision to cooperate and the propensity to generate successful innovations (de Faria et al., 2010). Therefore, we include a variable (R&D intensity), which is the natural logarithm of the ratio of total expenditures in R&D activities to total turnover, as a proxy for the intensity of a firm's devotion of resources to innovation activities.

According to the concept of absorptive capacity (Cohen & Levinthal, 1989, 1990), pre-existing knowledge and internal technological capacities are essential for the exploitation of the benefits of joint innovative activities. In the presence of internal technological capacities and capabilities, a firm can take advantage of and absorb incoming spillovers as long as there is not significant recontextualization (Brannen, 2004). Similarly, a well-prepared firm can better install appropriability mechanisms (e.g. patents, copyrights, trademarks, registered designs, complex product designs, or lead-time advantages) to protect outgoing spillovers (Cassiman & Veugelers, 2002). In order to capture these arguments about absorptive capacity, we include a variable for the level of education in a firm's workforce, called *tertiary education*.[18]

The firms' environment—including level of competitiveness and technological potential—affect their propensity to cooperate and innovate. In line with Abramovsky et al. (2009), we include a variable to approximate the level of competitiveness a firm is facing. We construct the variable *firm competiveness* as the share of exports on total turnover, where export attitude is a proxy for

[18] A detailed description of the variables can be found in Table 18 in Appendix 3.6.

competitiveness (de Faria et al., 2010). This assumes that a firm with high export ratios is embedded in a more competitive environment and also more likely to cooperate with external partners (Dachs et al., 2008). Following the theoretical argument and empirical findings that the technological environment in which a firm operates influences cooperation propensity and innovation performance (Bayona, Garcia-Marco, & Huerta, 2001; Miotti & Sachwald, 2003), our model contains a variable (technological potential) to control for different technology levels.

Firm size and other intrinsic factors are also influential for innovation activities. We include a firm size variable (firm size, log). However, the effect of firm size on the decision to engage in cooperative activities with external partners is ambiguous. Cohen & Levinthal (1990) state that with increasing firm size a firm possesses higher absorptive capacity and is able to devote more resources to innovation activities. Consequently, they argue that firm size is linked with a higher propensity to cooperate. Contrarily, Cassiman & Veugelers (2002) remark that with increasing firm size, the capabilities of a firm increase along with the possibility to conduct innovation activities internally without the necessity of including external parties. Thus, it is not a priori clear how firm size affects innovation performance. As younger firms are expected to be more innovative in order to gain market access, our model controls for firm age. Furthermore, our model includes dummy variables for industry affiliation, and survey years.

3.4 Results and discussion

3.4.1 Descriptive results

As can been seen from Table 14, 65.6% of the innovating firms conduct R&D and 23.5% cooperate with external partners over the five waves of the survey. The average number of different cooperation types is slightly above three. With respect to partner types, Table 16 in the Appendix 3.6 represents the shares of cooperating firms with cooperation arrangements with customers (average 62.5%), suppliers (68.5%), competitors (35.1%), non-competing firms (39.4%), firms from the same corporate group (41.5%), universities (54.7%), and other research institutions (28.5%) for each wave.

Table 14: Frequencies and percentages of firms successfully innovating, conducting R&D, and cooperating with external partners; as well as the average amount of cooperation partner types in 1999, 2002, 2005, 2008, and 2011.

		Thereof		Thereof
Years	Innovating	R&D	Cooperating	Collaboration partners
1999	1355 (62.4%)	891 (66.3%)	341 (38.5%)	3.31
2002	1539 (59.5%)	1075 (70.2%)	300 (19.6%)	3.15
2005	1488 (58.2%)	974 (65.5%)	372 (25.3%)	3.17
2008	1265 (59.7%)	768 (60.7%)	287 (22.7%)	3.51
2011	1274 (53.9%)	822 (64.5%)	320 (25.1%)	3.38
Total	6919 (58.6 %)	4528 (65.6%)	1621 (23.5%)	

3.4.2 Estimation procedure

We apply a random-effect panel Tobit model to estimate our model. Following other studies with similar data characteristics (e.g. Arvanitis & Bolli, 2012), we choose a Tobit estimation procedure because many firms do not have any sales with market novelties and hence our dependent variable would be characterized by a “corner solution” around 0. In order to derive unbiased estimates, we use a left-censored Tobit model with innovation performance as the dependent variable, downward censored at 0. The summary statistics can be found in Table 17 in the Appendix 3.6.

3.4.3 Impact of diversity in cooperation partners on innovation performance

Table 15 presents the results of the Tobit regression analysis with innovation output as the dependent variable. In model 1, the results show a positive and highly significant effect for the collaboration diversity variable. Model 2 exhibits a significant positive coefficient for *collab_diversity* and a significant negative coefficient for the squared term, indicating that there is a curvilinear relationship between diversity in types of cooperation partners and innovation performance.

Table 15: Tobit regression estimates for innovation output performance.

Dependent variable: Innovation performance	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.	Model 4 Coeff.
Collab_diversity	0.031***	0.108**	0.111**	0.104**
	(0.01)	(0.05)	(0.05)	(0.05)
Collab_diversity, squared		-0.165*	-0.167*	-0.185*
		(0.10)	(0.10)	(0.10)
Interaction (Collab_div.*R&D intensity)			-0.071	
			(0.19)	
Interaction (Collab_div.*smallFirm)				0.051**
				(0.03)
R&D intensity (logs)	1.833***	1.858***	1.962***	1.827***
	(0.44)	(0.44)	(0.53)	(0.44)
Missing R&D intensity (d)	-0.168***	-0.168***	-0.168***	-0.168***
	(0.05)	(0.05)	(0.05)	(0.05)
Tertiary education	0.004*	0.004*	0.004*	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)
Firm size (logs)	-0.042**	-0.044**	-0.044**	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Firm age (logs)	-0.094***	-0.092**	-0.092**	-0.091**
	(0.04)	(0.04)	(0.04)	(0.04)
Firm competiveness (logs)	0.588***	0.594***	0.594***	0.602***
	(0.11)	(0.11)	(0.11)	(0.11)
Technological potential	0.097***	0.097***	0.097***	0.097***
	(0.02)	(0.02)	(0.02)	(0.02)
7 industry dummies	$\chi 2$ (6)= 126.61***	$\chi 2$ (6)= 125.69***	$\chi 2$ (6)= 125.75***	$\chi 2$ (6)= 126.14***
5 survey year dummies	$\chi 2$ (4)= 25.83***	$\chi 2$ (4)= 25.25***	$\chi 2$ (4)= 25.33***	$\chi 2$ (4)= 24.99***
Constant	1.771***	1.779***	1.777***	1.719***
	(0.20)	(0.20)	(0.20)	(0.20)
N	4488	4488	4488	4488
Wald chi^2	414.09	417.54	417.61	421.96
Prob> chi^2	0.000	0.000	0.000	0.000
Log likelihood	-7520.618	-7519.168	-7519.100	-7517.131

Note: *, **, and *** denote significance at the 10%, 5%, and 1% test-level. Standard errors in parentheses. For all models, the number of left-censored observations is 510. (d), indicates a dummy variable.

In the next models, we include our interaction terms to analyze the moderating effects of internal absorptive capacity and firm size. Referring to model 3, we cannot detect a statistically significant moderating effect of internal absorptive capacity on sales with innovative products. For the moderating effects of firm size, the results in model 4 show a positive and significant coefficient for the interaction between small firms and the collaborative diversity variable as well as a positive and significant coefficient for *collab_diversity* and a negatively significant coefficient for the squared term. Consequently, the tipping point of the inverted U-shaped relationship shifts to the right.

In accordance with our expectations and in alignment with previous studies (e.g. de Faria et al., 2010), the results regarding R&D intensity show a significant positive effect between the resources invested in innovative activities and innovation output for all of our models. Our additional proxy for absorptive capacity—the proportion of employees with tertiary education in the firm's workforce—also positively influences innovation output. Moreover, the results indicate a negative impact of firm size and age on innovation output. In line with our expectations and previous empirical research (e.g. Abramovsky et al., 2009), we detect a strong positive and significant effect of firm competitiveness level on innovation outcome. Additionally, our analysis exhibits statistically significant evidence that higher levels of technological potential and opportunities relate to better innovation performance. The results further show strong economic sector affiliation effects.

3.4.4 Discussion

The results reinforce our assumption that diversity in types of cooperation partners matters for innovation performance. Evidently, firms can achieve performance enhancements with respect to innovation output with increased diversity in cooperation partner types. Therefore, hypothesis 3.1 can be confirmed. Turning to the potential risk of an over-diversified cooperation strategy causing negative returns in innovation output, we assumed a curvilinear relationship (inverted U-shape) between diversity in types of cooperation partners and innovation output. The results based on model 2 show statistical evidence for this functional form, and hypothesis 3.2 can be supported. These findings give support to our ideas that innovating firms can benefit from the know-how, resources, and capabilities of external partners, and that a wide diversity in types of cooperation partners in a cooperation network can enhance firm innovation output. However, this only applies to certain levels of diversity: an over-diversified cooperation network leads to decreasing returns. Finally, these findings support the importance of partner-type selectivity in the process of collaborative innovation.

To investigate in more detail how internal absorptive capacity—or more precisely how investments in R&D activities—moderates the relationship between diversity and innovation performance, we analyzed this moderating effect in a separate model. Although our model shows a negative coefficient for the interaction term indicating a substitution effect between R&D investments and engagement in external cooperation arrangements, we found no statistically significant evidence for this moderating effect. Recall, though, that our interaction variable does not represent internal investment in R&D but rather the overall expenditures in R&D, meaning that it also includes expenditures on external R&D activities.

To focus on how firm size influences the benefits of external cooperation agreements with different types of partners in a cooperation network, we analyzed the moderating effect of small firm size. With respect to the moderating effect of small size, we can state that small firms derive significantly greater advantages from diversity in cooperation partners as compared to other firm-size groups. As the tipping point shifts to the right, the results show that small firms benefit more from integrating a greater variety of external cooperation partner into their cooperation network.

There are numerous possible theoretical perspectives on the relationship of small firms to their cooperation networks, and this finding helps indicate useful directions. One idea was that small firms possess only limited internal capacity and resources to take advantage of a wide range of external sources of knowledge and that it is difficult for small firms to manage a manifold cooperation network; these findings are quite counterintuitive to that idea. Instead, these findings hint that, for small firms it may be less difficult to pay managerial attention to different types of partners than in larger firms. This in turn may suggest that small firms have less difficulty managing and controlling relationships to external partners, and that they are more likely to improve their innovation performance by complementing their internal resources and capabilities with external partners. One explanation for the higher effectiveness of small firms may be the fact that organizational issues are less complex and less bureaucratic for small firms (Jaruzelski et al., 2012), and as a result small firms are better able to convert ideas into innovative products. Another reason for the better performance of small firms may be because small firms are more effective in placing the right people with a good combination of experience, technology, and business sense in charge of managing collaborative relationships (Jaruzelski et al., 2012).

3.5 Conclusion and future research

This study investigates the influence of partner type diversity in collaborative networks on innovation output performance. Based on an econometric estimation using panel data from Swiss firms covering a time period from 1997 to 2011, the results show that innovating firms can benefit more with respect to innovation performance as measured by sales share of innovative products on total turnover from a diversified collaboration network than a more narrow strategy. Further, our analysis exhibits a tipping point indicating that the benefits from diversity decrease after a certain degree of saturation. Moreover, to the best of our knowledge, our study provides the first empirical evidence based on a large-scale cross-sectional panel data analysis that the relation between diversity in cooperation partner types and innovation performance follows a curvilinear relationship. In sum, despite the gains from diversity in cooperation networks, higher diversity can also be linked to risks such as protection of core technologies and appropriability mechanisms as well as to managerial attention problems for overseeing the manifold relationships to external partners, complex technology bases, and business opportunities located outside the firm.

In this way, our work contributes to a better understanding of the effects of firms' cooperation decisions on innovation performance. This additional knowledge is not only necessary for the development of appropriate innovation and technology policies that foster national competitiveness from a policy point of view, but also for the definition and creation of appropriate HRM and knowledge management policies and practices that facilitate and foster innovative activities in firms from a managerial point of view.

Overall, the findings support our theoretical reflections that firms are able to benefit in terms of increased innovation performance by complementing their internal resources and capabilities and gaining access to external partners. In a business environment in which firms are exposed to increasing competition from not only a national but also a global point of view, firms need to become successful innovators. In this regard, it is essential to identify effective mechanisms that help derive positive results from increasing diversity. Therefore, future research could deal with evaluating specific appropriability mechanisms influencing innovative capabilities (Ahuja et al., 2013). From a strategic management perspective, managerial decision makers should carefully evaluate the firm's cooperation strategy in order to find the balance between the advantages of special knowledge and technologies located outside the firm and the problems and risks associated with knowledge leaking out. HRM and knowledge management are challenged to create appropriate practices and policies enabling firms to better exploit their external cooperation network. Another area of future empirical research could elaborate how modern HRM practices—including HRM flexibility— affect innovative capabilities (see e.g., Way et al., 2012). Our study has further shown that the gains from diversity in cooperation network are moderated by firm size. However, there is still some need for future research. It is still unclear which mechanisms in smaller firms drive increased innovation performance. Future research should identify effective mechanisms and try to adapt them to larger enterprises.

In our study we have only taken into account the impact of the diversity of general types of cooperation partners, without consideration for the national origin of those partners. From one point of view, cooperation with international partners could enable firms to take advantage of special knowledge and technologies from abroad; on the other side international cooperation arrangements come with additional problems and risks such as cultural and social distance, and different intellectual protection rights and laws. Going one step further, future research could deal with the question of how cultural and social factors affect relationships in a cooperation network, and could investigate their impact on innovation performance.

3.6 Appendix

Table 16: Frequencies and shares of cooperating firms with respect to their types of cooperation partner.

Years	Cooperating	Customers	Suppliers	Competitors	Non- Competitors	Firms from same corporate group	Universities	Other Research Institutions
1999	341	199 (59.6%)	225 (67.4%)	136 (40.7%)	130 (38.9%)	141 (42.2%)	175 (52.4%)	101 (30.2%)
2002	300	176 (59.9%)	197 (67.0%)	111 (37.8%)	118 (40.1%)	114 (38.8%)	139 (47.3%)	72 (24.5%)
2005	372	221 (60.2%)	249 (67.9%)	129 (35.2%)	123 (33.5%)	150 (40.9%)	203 (55.3%)	88 (24.0%)
2008	287	194 (67.8%)	204 (71.3%)	97 (33.9%)	125 (43.7%)	122 (42.7%)	170 (59.4%)	93 (32.5%)
2011	320	207 (65.7%)	218 (69.2%)	87 (27.6%)	133 (42.2%)	135 (42.9%)	185 (58.7%)	101 (32.1%)
Total	1300	997 (62.5%)	1093 (68.5%)	560 (35.1%)	628 (39.4%)	662 (41.5%)	872 (54.7%)	455 (28.5%)

Table 17: Summary statistics, and cross correlation matrix of relevant variables.

		Obs.	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8
1	Innovation performance	4488	31.455	27.391	0	100								
2	Collab_diversity	4488	1.165	1.843	0	7	-	1.00						
3	R&D intensity (log)	4488	0.026	0.068	0	1.013	-	0.09	1.00					
4	Tertiary education	4888	-	-	-	-	-	0.14	0.30	1.00				
5	Firm size (log)	4488	375.503	2,163.585	1	60,000	-	0.22	-0.06	0.00	1.00			
6	Firm age (log)	4488	65.520	42.854	1	645	-	0.02	-0.14	-0.16	0.26	1.00		
7	Competitiveness (log)	4488	0.376	0.378	0	1.00	-	0.18	0.19	0.12	0.18	-0.05	1.00	
8	Technological Potential	4488	3.069	1.088	1	5	-	0.21	0.16	0.21	0.16	-0.07	0.23	1.00

Table 18: Description of relevant variables.

Variable	Description
Dependent variable	
lnInSales	Natural logarithm of the sales shares of innovative products (sum of the sales of new products and considerably modified products) on total turnover.
Independent variables	
Collab_Diversity	Continuous variable. Represents the firm's amount of different types of external cooperation partners. The number ranges between 0 and 7.
R&D intensity (log)	Natural logarithm of R&D expenditures divided by total sales.
Missing R&D intensity	Dummy variable; 1 represents firms with a missing value for R&D intensity. 0 otherwise.
Tertiary education	Share of employees with tertiary education on total workforce.
Firm size (log)	Natural logarithm of the amount of employees (full time equivalents).
Small firm	Dummy variable; 1 represents firms with a firm size smaller than 150. 0 otherwise.
Firm age (log)	Natural logarithm of firm age.
Competitiveness (log)	Represents the level of competitiveness measured as share of exports on total turnover.
Technological Potential	Nominal variable; represents the general technological potential, i.e. scientific and technological knowledge relevant to the firm's R&D or innovation activity (on a five point Likert-scale; 1 very low, 5 very high technological potential).
Construction	2-digit NACE classification code. Mining, construction, energy (10-14, and 40-41).
Consumer goods	Consumer goods (NACE code: 15-19)
Intermediate goods	Intermediate goods (NACE code: 20-27)
Investment goods	Investment goods (NACE code: 28-37)
Traditional services	Traditional services excluding hotels and restaurants (NACE code: 50-52; 60-64)
Knowledge-based services	Knowledge-based services (NACE code:65-67; 72-74)
Other services	Other services (NACE code: 55; 70-71; 80; 8511; 853; 90; 92)
Survey year 1999, 2002, 2005, 2008, and 2011	Dummy variable; 1 represents the relevant survey year period. 0 otherwise.

CHAPTER 4

Innovation outcomes and partner-type selection in R&D alliances: The role of simultaneous diversification and sequential adaptation

This chapter is co-authored with Cindy Lopes-Bento.

Abstract: This study focuses on how firms form and sequentially adapt their inter-organizational knowledge sourcing structures within research and development (R&D) alliances and how this process impacts their innovation performance. In contrast to the previous literature that mainly ignores the dynamic aspects of how firms adapt their search strategies, our approach accounts for sequential adaptation. Our proposed framework explores the role of simultaneous diversification and sequential adaptation of collaboration partners within R&D alliances according to specific innovation outcomes. The results emphasize that firms should not remain within the same search activities indefinitely, as non-adapting inter-organizational knowledge transfer structures lead to inferior performance. Notably, this study highlights important partner-type selectivity and identifies appropriate simultaneous diversification and sequential adaptation strategies in relation to specific innovation outcomes and firm sizes.

Keywords: Strategic alliances; organizational learning; sequential adaptation; simultaneous diversification; R&D collaboration; innovation strategy; innovation performance; radical innovation; incremental innovation.

4.1 Introduction

Today's highly competitive and rapidly changing market and technological environment challenge firms to effectively manage their innovation search activities. One of the strategies that firms undertake to respond to these challenges is to form strategic research and development (R&D) alliances with external partners to gain access to new technologies, complementary know-how and other additional resources (Gulati et al., 2000; Mowery et al., 1996). The ways in which firms are able to manage these inter-organizational structures of knowledge exchange and technology transfer with external sources are crucial for the firms' innovativeness and long-term competiveness, and this type of management represents a key aspect of managerial decision making and organizational learning (Argote & Ingram, 2000; Teece et al., 1997).

However, important issues remain: we must determine which structural patterns of R&D alliance partners are most appropriate to achieving specific innovation outcomes. Moreover, firms must decide how to organize the dynamic adaptation of collaboration partner types in R&D alliances. For instance, firms could maintain the same collaboration patterns to benefit from experience with the same partners, or they could adapt partners more frequently to be more dynamic, and therefore, able to react more quickly to changing market demands. These issues culminate in the focus of our study on how should firms simultaneous and sequentially select their collaboration partners in R&D alliances to meet specific objectives.

Despite the importance of these partner-type selection issues for firms' competitive advantage, surprisingly few studies have focused on their dynamic aspects (Bakker & Knoben, 2014; Belderbos, Carree, Lokshin, & Sastre, 2015; Katila & Ahuja, 2002). Even more surprisingly, little is known about the performance implications of the dynamic adaptation of R&D alliances. The objective of this paper is to fill this void by deriving a conceptual framework and empirically testing the role of simultaneous diversification and sequential adaptations of types of collaboration partners in R&D alliances to generate specific firm innovation outcomes, such as radical or incremental innovations. First, we focus on simultaneous patterns of inter-organizational collaboration, and our goal is to identify appropriate simultaneous diversification patterns of R&D partners to achieve specific firm innovation outcomes. Second, we focus on the sequential adaptation of R&D alliances and explore the effective sequential adaptation strategies of collaboration partner types to generate different innovation outcomes. A more profound understanding about which adaptation strategies are aligned to specific innovation outcomes is crucial for managers. This knowledge would increase managers' ability to effectively orient organizational resources along firms' innovation objectives of fostering either radical or incremental innovations. Finally, as the previous literature indicates that organizational learning is affected by the firm size, our conceptual framework accounts for different firm size classes (Arora, Belenzon, & Rios, 2014; Brunswicker & Vanhaverbeke, 2015; Patel & Pavitt, 1997; Zeng et al., 2010).

By enlarging the understanding of how simultaneous and sequential selections of collaboration partner types are associated to innovation outcomes, our study contributes to the literature on organizational learning, innovation strategies, and open innovation (Arora et al., 2014; Chesbrough, 2003a; Levitt & March, 1988). Hence, this study operates at the crossroads of the organizational learning and strategic alliance literature by linking the impact of various structural alliance compositions to innovation performance implications. In particular, we contribute to the literature on R&D alliances and organizational learning by providing new insights about the performance implications of the dynamic adaptation of R&D partners in strategic alliances. These structures and mechanisms of dynamic inter-organizational knowledge exchanges and technology transfers within R&D alliances are still unclear and deserve further research (Bakker & Knoben, 2014; Dahlander & Gann, 2010; Easterby- Smith, Lyles, & Tsang, 2008; Kale & Singh, 2009; Laursen & Salter, 2014).

To extend the conceptual understanding of inter-organizational knowledge exchanges and technology transfers within R&D alliances, we introduce the concepts of simultaneous partner diversification and sequential partner adaptation. Our approach links these concepts to different innovation outcomes and examines whether certain simultaneous diversification and specific sequential adaptation strategies are associated with superior innovation outcomes. The previous literature has largely acknowledged the use of interfirm R&D alliances to integrate technology-based capabilities and other forms of knowledge from external collaboration partners such as suppliers, customers, competitors or science centers (Kogut, 1988; Mowery et al., 1996). However, there is a lack of understanding of how different compositions of alliance partners influence the opportunities to enhance the technological capabilities and innovation performance of firms. In particular, there is a void in the empirical research with respect to how technological opportunities of firms are affected by inter-organizational structures of knowledge exchanges. Part of this void can be attributed to the difficulties in measuring changes in the technological potential of a firm (Mowery et al., 1996). To advance the knowledge in this field, this study introduces a new measure that accounts for a change in the firm's opportunities for technological capabilities and relates this measure to more traditional indicators of innovation outcomes such as radical and incremental innovation performance (Beck, Lopes-Bento, & Schenker-Wicki, 2014; Meuer et al., 2015).

In our study, based on a sample of 2,087 Swiss firms for the period 1999-2013 and stemming from Community Innovation Survey (CIS) data, we find evidence of partner-type selectivity in R&D alliances in relation to specific innovation outcomes. In addition, our results highlight the importance of firms effectively adapting their inter-organizational knowledge structures according to both specific innovation outcomes and their own sizes. Based on our findings, we can draw important managerial implications, and by systemically acknowledging the dynamics within R&D alliances, our study enlarges the development of an innovation theory that accounts for the organizational dynamics in firms' innovation activities.

4.2 Theoretical background and conceptual framework

4.2.1 Inter-organizational learning in R&D alliances

Organizations face the challenge of finding solutions for technological problems in changing market and technological environments. In addition to the possibility of solving a problem with the current routines and practices, organizations can initiate learning and search processes by including external sources of knowledge (March & Simon, 1958; Nelson & Winter, 1982). Overall, firms have the ability to make (internal R&D), buy (external R&D) or organize (R&D collaboration) the necessary knowledge and technology (Arora et al., 2014). Finding an optimal interplay between internal and external searches represents a fundamental facet of innovation theory and constitutes a crucial managerial task (Koka & Prescott, 2008; Laursen & Salter, 2014; Levinthal & March, 1993; Li & Rowley, 2002; Parmigiani & Mitchell, 2009; Rivkin, 2000; Teece et al., 1997).

Given the increasing importance of openness in the innovation process, re-combinations of existing solutions to solve new technological problems form a crucial part of innovation and are often found outside the boundaries of the firm. Open innovation practices cannot only be found in small and medium-sized enterprises (SME) (Brunswicker & Vanhaverbeke, 2015; Cerchione, Esposito, & Spadaro, 2015; Hottenrott & Lopes-Bento, 2014a; van de Vrande et al., 2009; Zeng et al., 2010), though SMEs may be more exposed to the lack of internal complementarities of resources, capabilities and know-how; instead, those practices are also present in large firms. An example of the effectiveness of this integrated approach of external knowledge sourcing in large firms is the case of Roche Diagnostics (Birkinshaw & Crainer, 2009). To gather experience on whether Roche is able to effectively harvest ideas and solutions from external sources of knowledge, Roche conducted an experimental learning challenge in which it compared the results of an R&D research team composed by exclusively internal R&D workers to the pay-offs of an integrated external community of R&D workers. The findings showed that by drawing on a mix of knowledge derived from internal and external networks, Roche was able to overcome their traditional search routines and could create some brilliant and unexpected solutions to apparently intractable problems.

The previous literature highlights that joint R&D activities with external partners in R&D alliances constitute an important mechanism in the process of organizational learning to create, retain and transfer knowledge (Argote, 2011; Gulati et al., 2000). These inter-organizational structures of knowledge transfers with different types of partners increase the complementarities of existing knowledge within the firm and can constitute an essential source of competitive advantage and dynamic capabilities (Teece et al., 1997). Empirical studies confirm the positive effects of these complementarities between different types of partners on the innovation performance (Belderbos, Carree, & Lokshin, 2006). However, very little is known about the complementarities and congruencies between different external partners and how to match them according to different innovation objectives, such as radical or incremental innovation outcomes. According to Teece et al. (1997), this recognition is critical to understanding organizational learning.

As argued above, different complementarities between collaboration partners can lead to different innovation outcomes. Our approach explicitly relates specific compositions of R&D alliances to different types of innovation outcomes.[19] According to Raisch and Birkinshaw (2008), a central aspect in the organizational literature regarding technological innovation is the distinction between incremental and radical innovation (Abernathy & Clark, 1985; Atuahene-Gima, 2005; Dewar & Dutton, 1986; Garcia & Calantone, 2002; Tushman & Anderson, 1986). Incremental innovations represent significant but relatively minor improvements or adaptations of existing products or business concepts. In contrast, radical innovations, as stated by Raisch and Birkinshaw (2008), "refer to fundamental changes leading to a switch from existing products or concepts to completely new ones."[20] Further studies have noted that organizations often

---

[19] The previous literature emphasizes the existence of major heterogeneities in the motives and objectives for collaboration (Belderbos et al., 2004a; de Faria et al., 2010; Kaiser, 2002; Tether, 2002). For instance, Belderbos et al. (2004b) show that collaboration with competitors or suppliers aims at enhancing labor productivity growth, whereas collaboration with universities or competitors can increase market novelties.

[20] In this line, other literature in the field of organizational ambidexterity (Raisch, Birkinshaw, Probst, & Tushman, 2009; Tushman & Smith, 2002) relates incremental

pursue both types of innovations. Scholars assume that effectively balancing both types of innovations can enhance dynamic capabilities and provide additional competitive advantage (Ancona, Goodman, Lawrence, & Tushman, 2001; Colbert, 2004). However, there are various organizational tensions (such as the “capability-rigidity paradox”) to finding an appropriate balance between different innovation objectives (Atuahene-Gima, 2005; Brown & Eisenhardt, 1997) and the interrelationships between internal and external knowledge sourcing processes (Cohen & Levinthal, 1990; Kogut & Zander, 1992; Lin, Yang, & Demirkan, 2007; Raisch et al., 2009). The present approach builds and extends the previous theory regarding the performance implications of inter-organizational structures of knowledge exchanges in relation to specific types of innovation outcomes.

4.2.2 Conceptual framework

Extending the current literature, our approach introduces the concepts of simultaneous partner diversification and sequential partner adaptation, and it connects these concepts of inter-organizational mechanisms of knowledge exchange with different firm innovation outcomes. Contrary to the previous studies in this field, our approach provides a conceptual framework to explicitly explore the role of dynamic adaptations of R&D collaboration patterns that are related to different innovation outcomes.

---

innovations to exploitive relationships and radical innovations to explorative relationships.

Simultaneous partner diversification

Our first key concept is simultaneous partner diversification. This concept refers to simultaneous partnership diversification within R&D alliances, and it explicitly accounts for the complementarity effects between collaborating partner types at the same time.

In our setting, a firm can use various collaboration partner types such as suppliers and customers (vertical partners), competitors (horizontal partners), or universities (scientific partners) in its search activities. Following the idea of communities of practices by Cook and Brown (1999a), each of these channels is aligned to different collaboration partner types and represents a separate search space with different institutional norms, habits, and rules; however, each channel also requires appropriate organizational practices to manage these partnerships effectively (Beck & Schenker–Wicki, 2014; Laursen & Salter, 2006). For instance, collaborating with end-users requires different skills, mind-sets, experience and knowledge than collaborating with an international research laboratory, including different intellectual property practices, norms of disclosure, and social and cultural attitudes. According to evolutionary economists (Metcalfe, 1994; Nelson & Winter, 1982), this variety and complementarity can help firms to find and create new combinations of technologies and knowledge. However, firms must be careful not to over-search, as over-searching can be related to the costs exceeding the benefits based on a certain threshold (Beck & Schenker–Wicki, 2014; Laursen & Salter, 2006). For instance, lacking managerial expertise and ineffective managerial attention may lead firms to not select the right partners and to coordinate inefficiently (Katila et al., 2008).

While some previous studies, such as Belderbos et al. (2006), take the complementary composition of R&D collaboration into account, they do not relate these patterns to different degrees of innovation novelty. Although other studies account for different degrees of innovation novelty created by knowledge sourcing strategies (Laursen & Salter, 2006), they ignore the structural composition of complementary partnerships within R&D alliances. Thus, our approach combines these two perspectives and interrelates simultaneous partner diversification with different types of innovation outcomes.

In summation, after acknowledging the existence of complementarity effects between collaboration partner types, it remains unclear which combinations of partner types are associated with which innovation outcomes. In our framework, we argue that specific simultaneous diversification patterns are more appropriate to achieving different types of innovation outcomes. In this vein, we expect that firms that manage to organize their external knowledge exchanges with the best potential complementarity mix between the focal firms' resources, capabilities, and innovation objectives and their partners' resources and know-how show superior innovation performance. This expectation leads to the following hypothesis:

Hypothesis 4.1: Simultaneous partner diversification within R&D alliances is associated with specific innovation outcomes, and this relationship shows important partner-type selectivity effects.

Sequential partner adaptation

Our second key concept refers to sequential partner adaptation. Some scholars note that if we ignore sequential adaptation, the extent of the complementarity effects between collaboration partner types will not be fully taken into account (Battisti, Colombo, & Rabbiosi, 2014; Jovanovic & Stolyarov, 2000; Smith, 2005). Our approach accounts at least partly for the dynamics within R&D alliances and contributes to the reasoning on how routines and path-dependent behavior in firms' knowledge sourcing strategies is related to innovation outcomes in changing external environments (Koka & Prescott, 2008; Li & Rowley, 2002).

As some studies argue that long-term firm success requires an organizational balance between continuity and change (Brown & Eisenhardt, 1997; Raisch & Birkinshaw, 2008), we expect superior performance in those firms that sequentially adapt their organizational knowledge sourcing structures. Accordingly, the next hypothesis is as follows:

Hypothesis 4.2: Firms that sequentially adapt their collaboration patterns in R&D alliances exhibit superior innovation performance compared to firms that persist in having the same collaboration patterns.

We extend this reasoning and argue that firms should not only change their collaboration patterns over time, but should also pay attention to where to search for new knowledge and technology. To that end, the (dynamic) selection among different collaboration partner types is relevant. The previous literature on collaboration indicates a major heterogeneity between partners and emphasizes that where to search is relevant for innovation (Belderbos et al., 2004a; Cassiman & Veugelers, 2006; Kaiser, 2002). Following this logic, we argue that heterogeneity is not only important in the simultaneous selection of partners but also in the dynamic adaptation of collaboration partners. Consequently, we expect that in addition to changing their collaboration patterns, it is important for firms to adapt their collaboration partners effectively and to select appropriate partners to achieve specific innovation outcomes. This notion leads to the following hypothesis:

Hypothesis 4.3: R&D alliances exhibit important partner-type selectivity effects with respect to the impact and direction of sequential adaptation of collaboration partner types and the associated innovation outcomes.

Firm size

Several scholars have noted that the relationship between inter-organizational structures of knowledge exchange and innovation depends on the firm size (Arora et al., 2014; Beck & Schenker–Wicki, 2014; Belderbos et al., 2006). The literature also notes that the firm’s size may be linked to features such as its absorptive capacity or previous alliance experience (Sampson, 2005). Hence, we observe characteristics that are aligned to influence the outcomes of R&D collaborations. In our next step, we take the firm size into account to analyze the sensitivity of our results to these characteristics. While these studies refer to simultaneous structures of knowledge exchange (Beck & Schenker–Wicki, 2014; Belderbos et al., 2006), there are several reasons why we argue that the firm size also affects the role of the sequential adaptation of knowledge structures for specific innovation outcomes.

First, change and transformation processes are related to costs (Teece et al., 1997). Second, these processes require managerial attention (Ocasio, 1997) and coordination (Atuahene-Gima, 2005). These aspects demand financial and managerial resources that are differently allocated between SMEs and large firms. Hence, the ability and capacity to manage reconfigurations of knowledge structures may depend on characteristics that are aligned with firm size. Overall, we expect that the role of simultaneous partner diversification and sequential partner adaptation in achieving specific innovation outcomes will vary based on the firm size. These arguments lead to the following hypothesis:

Hypothesis 4.4: The relationship between simultaneous diversification, sequential adaptation in R&D alliances and the associated innovation outcomes is moderated by the firm size.

4.3 Data and methods

4.3.1 Sample

The empirical analysis uses data that are derived from the Swiss Innovation Survey. This survey has been conducted every three years by the Swiss Economic Institute (KOF) at the ETH Zurich since 1990. The survey is part of the European Community Innovation Survey (CIS) of the European statistical office (Eurostat) and follows the guidelines described in the Oslo manual developed by the Organisation for Economic Co-operation and Development (OECD) (OECD, 1997). This dataset provides us with a representative sample of Swiss firms with at least five employees from both the manufacturing and service industries. The sample contains firm-level information on innovation activities, R&D expenditures, knowledge sourcing, intellectual property practices, and performance measures among many other firm characteristics. The CIS and the Swiss Innovation Survey constitute a reliable, valid and well-established source of information on firms' innovative activities and commercial success. Indeed, the datasets derived from these surveys have been used in a wide range of recent and prominent studies (Arvanitis, 2012; Beck et al., 2014; Cassiman & Veugelers, 2002; Laursen & Salter, 2006; Leiponen & Helfat, 2010; Meuer et al., 2015). In our analysis, we use information from six consecutive waves covering a time period from 1999 to 2013. The postal survey received response rates of 33.8 % (1999), 39.6 % (2002), 38.7 % (2005), 36.1 % (2008), 35.9 % (2011), and 32.7 %

(2013).[21] After eliminating the missing values, we restrict our sample to those firms that are observed at least in two consecutive waves. In total, our dataset comprises 3993 observations from 2087 different firms.

4.3.2 Empirical strategy

In our analysis, we focus on the role of simultaneous diversification and sequential adaptation strategies in R&D alliances in firms' innovation performance. Our models measure how firms' innovation outcomes are associated with specific simultaneous diversification and sequential adaptation strategies as well as other firm characteristics. Because firms make their managerial choices about their diversification and adaptation strategies based on different innovation objectives, we account for three different innovation outcomes to evaluate the effectiveness of these diversification and adaptation strategies, namely, the firm's relative technological potential, radical innovation and incremental innovation output.

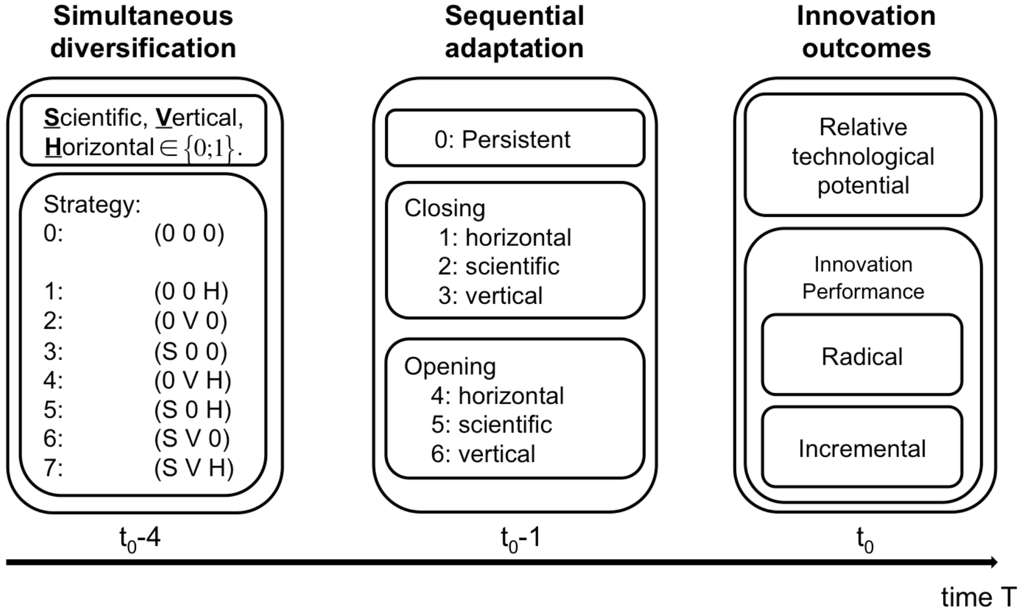
Following the previous literature, we define the radical innovation performance as the share of generated sales attributed to innovative products that are new to the firm, and we define the incremental innovation performance as products that are

[21] From 1999 until 2011, the survey was conducted every three years, but from the beginning of 2013 the Swiss Economic Institute changed the timing of the survey to every two years. The structure of the responses for different industry affiliations, regions, and sizes are largely consistent with the previous surveys. An overview on the innovation surveys from 1999 to 2013 and the corresponding innovation activities of Swiss firms from 1997 to 2012 can be found in Arvanitis et al. (2014).

significantly improved (Beck et al., 2014; Garcia & Calantone, 2002; Meuer et al., 2015). Accounting for the firm's relative technological position, we introduce a new measure that indicates if a firm is able to improve its technological potential towards the technological frontier within an industry. This measure of technological opportunities has so far not received much attention in the empirical literature (Teece et al., 1997). However, we acknowledge that firms choose their collaboration strategy to devise a solution to a certain technological shortcoming (Mowery et al., 1996), and we believe that accounting for the effectiveness of enhancing the technological potential indicates a good measure of the success or failure of different collaboration strategies. By including this measure, we expect to derive additional insights on how firms can improve their technological capabilities through collaboration.

With respect to our concepts of simultaneous diversification and sequential adaptations of collaboration partner types in R&D alliances, we differentiate between eight simultaneous diversification and seven sequential adaptation strategies (see Figure 1). For the simultaneous diversification of collaboration partner types, the exclusive combinations of vertical, horizontal, and scientific collaboration compose the eight strategies. The sequential adaptation strategies are characterized by either remaining persistent within the current pattern or opening towards or shunning vertical, horizontal or scientific partner types.

Figure 2: Conceptual framework



Given the strong unbalanced nature of our panel dataset, we make use of the pooled cross-sectional structure of our data to estimate our models. We use robust clustered standard errors to account for the potential correlations of the errors, and we include a substantial set of control variables. For our first outcome measure that indicates the relative technological potential, we estimate probit models such that the dependent variable for the relative technological potential of a firm equals one if its technological potential is higher than the firms' average in a given period. The binary response models are estimated as follows:

$$y_i^* = x_i\beta + \varepsilon_i \qquad (4.3.1)$$

$$y_i = 1[y_i^* > 0], \varepsilon_i \sim \mathcal{N}(0, \sigma^2)$$

where the binary variable y_i indicates the sign of the unobserved latent variable y_i^*.

For the equations that estimate firms' innovation performance, we apply pooled regression models with radical and incremental innovation performance as the dependent variables. These variables are measured as the ratio of the radical (incremental) innovative sales to the total turnover. Because these variables by definition range between 0 and 100, and because not all firms have innovative sales in each period, our data are characterized by corner solution outcomes around 0 (Winkelmann & Boes, 2006; Wooldridge, 2010). For our analysis, we use Tobit models to account for these censored dependent variables. With our approach, we are in line with previous empirical studies that faced similar data characteristics (Bakker & Knoben, 2014). As argued in Greene (2003), standard Tobit models require the assumption of homoscedasticity. As LR tests of the residuals indicate violations of the homoscedasticity assumption in our setting, we model the group-wise multiplicative heteroscedasticity by including firm size and industry dummies.[22] The Tobit models are estimated as follows:

$$InnoPerf_i^* = X'_{i,t-1}\beta + \epsilon_i, \qquad \epsilon_i \sim i.i.d.N(0,\sigma^2) \qquad (4.3.2)$$

$$InnoPerf_i = \begin{cases} InnoPerf_i^* \;\; if \; X'_{i,t-1}\beta + \epsilon_i > 0 \\ 0 \; otherwise \end{cases} \qquad (4.3.3)$$

where $InnoPerf_i$ represents the non-negative observable innovation performance variable; this variable captures the radical innovation and incremental innovation

[22] We therefore estimated the heteroscedasticity-robust model by a maximum likelihood function in which we replace the homoscedastic standard error term σ with σ_i = σexp(Z'α) in the likelihood function.

performance for the firm i. $InnoPerf_i$ corresponds to the latent dependent variable $InnoPerf_i^*$ if this variable is above zero and to zero otherwise. Finally, to avoid direct simultaneity, we run our analysis by allowing for time lags between the simultaneous diversification, sequential adaptation and output measures, as shown in Figure 2.

4.3.3 Measures

Dependent variables

We measure three different innovation outcomes to account for the different types of innovation objectives of firms. First, the *relative technological potential* (*RELTECHPOT*) captures reflections on pushing the technological capabilities of a firm above the industry average and thereby closer to the technological frontier of an industry (Teece et al., 1997; Tushman & Anderson, 1986). A dummy variable takes the value of one if the relative technological potential is above this threshold. Therefore, the level of the general technological potential of a firm reflects the level of scientific and technological knowledge available to it for conducting innovation activities (Kogut, 1988; Kogut & Zander, 1992; Mowery et al., 1996).

In addition, two further outcome variables indicate the firm's sales performance with innovative products and measure the commercial success of its innovation activities. In line with the previous literature (see, for instance, Laursen and Salter (2006)), we distinguish between radical and incremental innovation performance. Following Meuer et al. (2015), radical innovation performance

(*RADICAL*) is measured as the firm's sales share of radical innovative products, i.e., products that are new to the firm, to the total turnover. Similarly, the incremental innovation performance (*INCREMENTAL*) is measured as the fraction of the firm's turnover with incremental innovative products, i.e., products that are significantly improved.

Main explanatory variables

As a central part of our conceptual model, we account for the firm's diversification and adaptation strategies to search for external sources of knowledge through external collaboration partners. Therefore, we include various variables to capture our concepts of simultaneous partner diversification and sequential partner adaptation.

As a starting point, we introduce the variable DIVERSIFICATION to capture the firm's simultaneous collaboration pattern. To construct this variable, we use information about firms' different R&D collaboration agreements with external collaboration partners such as suppliers, customers, clients, competitors, universities, and other research institutes. Following Belderbos et al. (2004a), we aggregate this information and create three dummy variables that are each equal to 1 if a firm collaborates with a specific partner type. More precisely, we differentiate between vertical (*VERT*, suppliers, clients or customers), horizontal (*HOR*, competitors), and institutional scientific partner types (*SCIE*). Then, the simultaneous diversification pattern (*DIVERSIFICATION*) is uniquely defined by eight different combinations as shown in Figure 2. Consequently, the simultaneous partner diversification variable represents the complementarities between different partner type structures and the diversification within a firm's collaboration pattern (see Figure 2).

However, we do not stop at the simultaneous pattern; we also take dynamic behavior into account. With respect to this second concept, the sequential partner adaptation (*ADAPTATION*) analyzes what happens if a firm changes its collaboration pattern between two points in time (t_0-4 and t_0-1). Thus, the sequential ADAPTATION accounts for a firm modifying or locking down its pattern between two periods (i.e., times t_0-4 and t_0-1). Accordingly, a sequential adaptation in the firm's collaboration pattern can be described by seven different sequential adaptation strategies: a firm can remain persistent within its pattern or it can open to or shun horizontal, scientific, and vertical partner types (see Figure 2).

Overall, the introduction of these two new concepts captures the diversification and sequential adaptation of firms' collaboration patterns, which will enhance our understanding of the mechanisms between external knowledge sourcing and the innovation outcomes of firms.

Further controls

In our analysis, we further control for various factors that may influence firms' innovation outcomes. We include a measure for the firm's R&D investments: they are measured as the firm's R&D expenditures relative to its total turnover

(*RDINT*). This measure accounts for the firm's R&D activities, thereby reflecting its general absorptive capacity and ability to conduct innovative activities. The receipt of public support is indicated by a dummy (*PUBSUB*). A previous reception of a public grant signals relevant competences and capabilities to successfully conduct R&D projects to other partner firms, and hence, may affect innovation success.

Furthermore, we include the firm age (*FIRMAGE*) and (the log of) the firm size (*LNFIRMSIZE*) to capture relevant firm characteristics. Moreover, we include the squared term of the two previously mentioned variables to take a non-linear relationship into account (*FIRMAGE2, LNFIRMSIZE2).* In addition, we control for whether or not a firm belongs to a foreign group (*FOREIGN*), as foreign group members may show higher innovative performance due to spillovers from international group members. We also control for the foreign market activities of a firm. Highly export-oriented firms may be more innovative due to higher international competition than firms exclusively operating on a national market. We include a variable measuring the export share of the total turnover (*EXPORT*).

Moreover, seven industry-sector dummies account for the different propensities to innovate across sectors. Finally, we include six survey-year dummies in our set of control variables to control for time shocks.

4.3.4 Descriptive results

Relevant variables

Table 19 reports descriptive statistics about the relevant variables for our analysis. The table shows that on average, firms generate approximately 7.0 % of their total turnover with radical innovative products, whereas 8.2 % of the turnover can be attributed to incremental innovative products. Moreover, 50.8 % of the firms in our sample innovate, 37.6 % conduct R&D activities, and 14.2 % collaborate in R&D alliances. Among the firms in our sample, 8.6 % collaborate with partners from scientific institutes, 13.0 % collaborate with vertical partners, and 4.4 % collaborate with horizontal partners. On average, the firms in our sample are rather large (mean: 257 employees) and old (mean: 67 years). In addition, 85.1 % of the firms are SMEs. Further descriptive statistics of the industry and firm-size-class distribution are provided in Table 24 and Table 25 in Appendix 4.6.

Simultaneous partner diversification

After examining the descriptive results regarding the simultaneous partner diversification strategies in Table 20, we recognize that the predominant pattern in our sample is non-collaboration. After differentiating between firm size classes, the table shows that large firms collaborate more than SMEs. Diversification strategies that include vertical partners are frequently used, particularly within large firms. Moreover, large firms most frequently collaborate with scientific and vertical partners or all three partner types. Contrarily, SMEs are predominantly engaged in R&D alliances composed by scientific and vertical partner types or vertical partners alone.

Sequential partner adaptation

Focusing on sequential partner adaptation, our sample demonstrates that the most predominant strategy for firms is remaining persistent (see Table 21). This pattern appears particularly valid for SMEs, while large firms adapt their knowledge sourcing strategies more often. Overall, we observe the most frequent adaptations in R&D alliances towards opening up to or shunning vertical partner types.

Table 19: Descriptive statistics of the relevant variables.

	Variable	Obs.	Mean	S.D.	Min.	Max.
1	RADICAL	3993	6.951	13.665	0	100
2	INCREMENTAL	3993	8.208	15.580	0	100
3	RELTECHPOT	3993	0.522	0.500	0	1
4	R&D	3993	0.376	0.485	0	1
5	COLLABORATION	3993	0.142	0.349	0	1
6	INNO	3993	0.508	0.500	0	1
7	SCIENCE	3993	0.086	0.280	0	1
8	VERTICAL	3993	0.130	0.337	0	1
9	HORIZONTAL	3993	0.044	0.205	0	1
10	RDINT	3993	1.118	4.748	0	178.79
11	FIRMSIZE	3993	256.821	1749.612	1	43038
12	FIRMAGE	3993	67.401	42.146	2	614
13	EXPORT	3993	22.451	33.522	0	100
14	FOREIGN	3993	0.148	0.355	0	1
15	SUBSIDY	3993	0.059	0.235	0	1

Table 20: Descriptive statistics on simultaneous partner diversifications according to firm size classes.

Simultaneous DIVERSIFICATION	Full sample		Small-medium		Large firms	
STRATEGY: (S V H)	Freq.	Percent	Freq.	Percent	Freq.	Percent
0: (0 0 0)	3,429	85.88	3014	88.65	415	69.98
1: (0 0 H)	13	0.33	10	0.29	3	0.51
2: (0 V 0)	126	3.16	102	3.00	24	4.05
3: (S 0 0)	16	0.4	12	0.35	4	0.67
4: (0 V H)	74	1.85	56	1.65	18	3.04
5: (S 0 H)	8	0.2	7	0.21	1	0.17
6: (S V 0)	225	5.63	138	4.06	87	14.67
7: (S V H)	102	2.55	61	1.79	41	6.91
Total	3,993	100	3,400	100	593	100

Table 21: Descriptive statistics on sequential partner adaptations according to firm size classes.

		Full sample		Small-medium		Large firms	
Sequential ADAPTATION		Freq.	Percent	Freq.	Percent	Freq.	Percent
	0 persistent	3,322	83.20	2906	85.47	416	70.15
closing	1 horizontal	38	0.95	28	0.82	10	1.69
	2 scientific	38	0.95	29	0.85	9	1.52
	3 vertical	257	6.44	187	5.50	70	11.80
opening	4 horizontal	37	0.93	23	0.68	14	2.36
	5 scientific	44	1.10	33	0.97	11	1.85
	6 vertical	257	6.44	194	5.71	63	10.62
	Total	3,993	100	3,400	100	593	100

4.4 Empirical results

Table 22 presents the results of the regressions models, which reflect the role of simultaneous partner diversifications and sequential partner adaptations for different innovation outcomes. For the effects of simultaneous partner diversification, we find strong support for our first hypothesis, which indicates the presence of important selectivity effects. Precisely, our results indicate that certain simultaneous compositions of collaboration partners are more appropriate for specific innovation outcomes than others.

If firms intend to increase their relative technological potential (*PROBIT model*), we can state that scientific or horizontal partners are appropriate partner types in R&D alliances. However, to unfold the benefits, these partner types need to be complemented with vertical partners. Highly diversified collaboration patterns in R&D alliances that include collaborations with all three partner types are linked with the highest probability of increasing a firm’s relative technological potential.

With respect to our innovation performance measures, our analysis highlights that a pure vertical collaboration without any complementary partner is positively associated with performance gains in radical and incremental innovation output. Interestingly, a pure horizontal collaboration is negatively linked to an incremental innovation outcome, which may indicate potential leaks of knowledge or product collusion problems in the output market.

Scientific and horizontal collaborations only exhibit positive effects on radical and incremental innovation performance if they are complemented with vertical partners. Highly diversified patterns in R&D alliances composed by collaborations with scientific, horizontal and vertical partners also show positive effects on both types of innovation performance outcome. Notably, we find that a collaboration in R&D alliances with scientific partners or horizontal partners needs to be complemented with other partner types (i.e., with vertical partners) to enhance the positive effect on both types of innovation performance. This result is in contrast to vertical collaboration, which does not need to be complemented with other partner types. Overall, these results confirm our expectations about the presence of important selectivity issues with respect to the simultaneous partner diversification (*Hypothesis 4.1*).

Second, for the role of sequential partner adaptations in R&D alliances for firms' innovation outcomes, in accordance with our expectations the results generally show that firms can benefit through a sequential change in collaboration patterns (*Hypothesis 4.2*). However, not all of the results point in the same direction, and hence, hypothesis two can only partly be supported. For instance, we see that ending a scientific collaboration is negatively linked to the probability of enhancing the relative technological potential of a firm. Despite this negative impact, we mainly find positive effects of adaptation on innovation outcomes compared to remaining persistent.

These ambiguous results motivate us to more closely examine the partner-specific adaptation effects (*Hypothesis 4.3*). In this vein, our analysis unveils positive effects of ending scientific and horizontal collaborations for incremental innovation performance, indicating that these types of collaboration may not be the most appropriate partner type to collaborate with if firms intend to incrementally innovate. Furthermore, our results show positive effects of opening a horizontal collaboration for radical innovation outcomes. Finally, collaborating with vertical partners is overall positively linked with all three innovation outcome measures and seems to be an essential source of knowledge in R&D alliances. Ultimately, these results support hypothesis three of this paper by indicating significant partner selectivity effects.

Table 22: Regression estimates for innovation outcomes accounting for simultaneous partner diversification and sequential partner adaptation.

		Innovation outcomes		
		Probit	Random Effects Tobit	
Explanatory variables		RELTECHPOT	RADICAL	INCREMENTAL
DIVERSIFICATION (S V H) 0:		(.)	(.)	(.)
	1: (0 0 H)	0.397	9.653	-21.842***
		(0.468)	(6.288)	(8.458)
	2: (0 V 0)	0.266	10.296***	11.265***
		(0.174)	(2.499)	(2.968)
	3: (S 0 0)	0.307	-2.569	-10.411
		(0.336)	(5.772)	(7.300)
	4: (0 V H)	0.544**	11.171***	16.148***
		(0.217)	(3.237)	(3.728)
	5: (S 0 H)	0.476	13.822	2.766
		(0.530)	(8.689)	(11.441)
	6: (S V 0)	0.672***	7.189***	7.074***
		(0.155)	(1.985)	(2.415)
	7: (S V H)	0.809***	8.497***	7.828**
		(0.255)	(2.804)	(3.397)
ADAPTATION	0: persistent	(.)	(.)	(.)
	1 horizontal	0.014	-1.792	12.616**
		(0.361)	(4.262)	(5.204)
closing	2 scientific	-0.447*	6.400	9.237*
		(0.254)	(4.066)	(4.857)
	3 vertical	-0.223	0.953	0.397
		(0.164)	(2.128)	(2.536)
	4 horizontal	-0.019	6.894*	4.721
		(0.272)	(3.521)	(4.425)
opening	5 scientific	0.169	2.055	1.711
		(0.242)	(3.642)	(4.246)
	6 vertical	0.357***	11.237***	16.543***
		(0.100)	(1.515)	(1.817)
	CONTROLS	[YES]	[YES]	[YES]
	TIME DUMMIES	[YES]	[YES]	[YES]
	INDUSTRY DUMMIES	[YES]	[YES]	[YES]
	No. of observations	3,993	3,993	3,993

Note: The standard errors are clustered at the firm level, as firms appear more than once in the sample. The time and industry dummies are jointly significant (not presented). ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Firm size

In the next step of our analysis, we investigate the effectiveness of inter-organizational knowledge exchange structures that depend on the sizes of firms. Table 23 reports the results of simultaneous partner diversification and sequential partner adaptation after differentiating between SMEs and large firms.

Overall, our results demonstrate that the partner structure impacts the innovation performance differently according to the firm size (*Hypothesis 4.4)*. With regard to horizontal collaboration, pure horizontal collaboration represents an appropriate means for large firms to achieve high relative technological potential. However, this type of collaboration demonstrates negative effects on incremental innovation performance. Thus, although a horizontal collaboration is an essential source to gain technology potential, it comprises severe risks and threats for the economical commercialization if this collaboration engagement is undertaken to generate outcomes with only a minor degree of innovation novelty.

With respect to small firms, collaboration patterns that exclusively include vertical partner types are positively associated with higher relative technological potential, radical and incremental innovation performance, while this inter-organizational knowledge sourcing and transfer structure does not exhibit significant effects for large firms. In line with the full firm sample results, we cannot detect any statistically significant positive effect of a scientific collaboration if it is not complemented with other partner types for SMEs as well as for large firms. This finding highlights that this source of external knowledge alone enhances neither the relative technological potential of a firm nor its economical innovation performance. Consequently, this finding shows that scientific partners need complementary types of partners to exploit the knowledge received through scientific partners.

Next, we focus on the results of diversified patterns that are composed by more than one partner type. To begin with SMEs, our analysis shows that horizontal collaboration complemented with vertical partner types seems to be an effective external knowledge sourcing structure. This structure can not only enhance the relative technological potential, it can also boost the economical innovation performance with radical and incremental innovative products. Moreover, if it is complemented with a vertical partner, a scientific collaboration is positively associated with higher relative technological potential and radical innovation performance. Notably, inter-organizational R&D alliances composed by highly diversified partner structures composed of all three partner types are positively linked with a higher relative technological potential as well as with higher radical and incremental innovation performance.

For large firms, collaboration constellations with scientific and vertical partner types positively affect the relative technological potential and incremental innovation performance. Interestingly, large firms generally do not benefit to the same extent from the complementarity effects created from external partner types to enhance the firms' technological potential and innovation performance as SMEs. This finding highlights the scarcity of resources in SMEs, and hence, it indicates that collaboration may be an appropriate means for SMEs to confront these problems.

In shedding light on the sequential partner adaptation, our study detects substantial firm size effects. For instance, closing down a scientific collaboration is negatively linked with the relative technological potential, but positively associated with incremental innovation performance for SMEs. For large firms, no significant effect is found for any of the outcome variables. Although a scientific collaboration is an important source for higher relative technological potential for SMEs, these results point to the difficulties SMEs face in exploiting knowledge from scientific collaborations particularly if this inter-organizational knowledge exchange is supposed to foster incremental innovations. Contrarily, if large firms adapt their collaboration patterns and open up to scientific partners, our results shows positive effects for the relative technological potential as well as for both types of innovation performance. These results indicate that large firms are able to create benefits from collaborations with scientific partners for any type of innovation outcome. Hence, this knowledge and learning channel to scientific partners constitutes an important source of the competitive advantage of large firms.

With respect to SMEs, sequential adaptations in the form of opening toward horizontal collaboration partners show a positive effect on the radical innovation performance. This finding indicates that SMEs can benefit from joint collaborations with competitors for radical innovation to establish new technologies or standards and to create new output markets for these radical innovations. The insignificant effects for this sequential adaptation strategy for large firms may derive from the fact that large firms have less need for other external partners to shape these output markets.

Another interesting effect of sequential adaptation related to horizontal collaboration concerns large firms: closing down horizontal partnerships is linked to increased incremental innovation performance. This result shows that collaborations with competitors may harm large firms if the associated innovation outcome is incremental. This possibility may be due to potential collusion in the subsequent product market, increased leakage of knowledge to competitors, or ineffective appropriation mechanisms. Overall, we can conclude that the above findings with respect to the firm size are generally consistent with hypothesis four.

Table 23: Regression estimates for the innovation outcomes accounting for simultaneous partner diversifications and sequential partner adaptations and differentiating between small-medium-sized and large firms.

		Innovation outcomes					
		SMALL MEDIUM FIRMS			*LARGE FIRMS*		
		Probit	Random Effects Tobit		Probit	Random Effects Tobit	
Explanatory variables		RELTECHPOT	RADICAL	INCREMENTAL	RELTECHPOT	RADICAL	INCREMENTAL
DIVERSIFICATION	0 (S V H)	(.)	(.)	(.)	(.)	(.)	(.)
	1: (0 0 H)	0.132	7.171	-18.252	0.000	14.562	-27.061**
		(0.549)	(8.639)	(11.859)	(.)	(10.004)	(11.011)
	2: (0 V 0)	0.370*	14.651***	13.994***	0.129	-1.899	-4.819
		(0.203)	(3.113)	(3.590)	(0.340)	(4.497)	(5.317)
	3: (S 0 0)	0.615	-5.676	-11.158	-0.858	-1.126	-16.821
		(0.431)	(7.131)	(8.874)	(0.699)	(9.912)	(11.853)
	4: (0 V H)	0.699***	15.747***	15.577***	0.142	-2.587	8.225
		(0.241)	(3.990)	(4.605)	(0.487)	(5.362)	(5.699)
	5: (S 0 H)	0.444	5.232	-8.320	0.000	47.442	29.370
		(0.564)	(9.728)	(12.745)	(.)	(32.416)	(36.158)
	6: (S V 0)	0.640***	9.135***	4.854	0.830***	4.268	8.290**
		(0.205)	(2.884)	(3.383)	(0.236)	(2.704)	(3.316)
	7: (S V H)	1.305***	8.999**	9.593**	0.493	5.015	0.649
		(0.306)	(3.924)	(4.503)	(0.390)	(3.942)	(4.910)

ADAPTATION	0 persistent						
	1 horizontal	0.311	-2.959	9.265	-0.265	5.058	16.098**
		(0.462)	(5.760)	(6.889)	(0.558)	(6.396)	(7.569)
closing	2 scientific	-0.632**	7.831	10.441*	0.223	-2.335	4.720
		(0.318)	(5.027)	(5.822)	(0.511)	(7.175)	(9.104)
	3 vertical	-0.350*	-1.577	1.275	-0.039	4.664	0.142
		(0.198)	(2.845)	(3.295)	(0.297)	(3.195)	(3.919)
	4 horizontal	0.045	9.830**	8.050	-0.235	6.067	0.353
		(0.324)	(4.972)	(6.199)	(0.489)	(4.976)	(5.906)
opening	5 scientific	-0.118	-3.752	-5.665	0.000	16.626***	20.200***
		(0.268)	(4.481)	(5.176)	(.)	(6.411)	(7.000)
	6 vertical	0.253**	12.230***	15.494***	0.846***	8.986***	15.089***
		(0.110)	(1.840)	(2.143)	(0.250)	(2.576)	(3.307)
	CONTROLS	[YES]	[YES]	[YES]	[YES]	[YES]	[YES]
	TIME DUMMIES	[YES]	[YES]	[YES]	[YES]	[YES]	[YES]
	INDUSTRY DUMMIES	[YES]	[YES]	[YES]	[YES]	[YES]	[YES]
	No. of observations	3,400	3,400	3,400	569	593	593

4.5 Discussions, implications and concluding remarks

4.5.1 Discussion

As a response to today's highly competitive and rapidly changing environment, which includes shorter product cycles and time to market, firms need to adapt effectively to meet these challenges (Bakker & Knoben, 2014; Mohammed & Nadkarni, 2011). One of the response strategies for many firms is to form strategic inter-organizational R&D alliances with external collaborating partners. This study extends the conceptual understanding of inter-organizational structures of external knowledge exchanges and technology transfers within R&D alliances. To that end, we introduce two new concepts, namely, simultaneous partner diversification and sequential partner adaptation.

The introduction of these concepts should help achieve a better evaluation of the managerial choices of strategies to organize external knowledge sourcing and transfers through collaboration to effectively meet specific innovation objectives. As we expected, these knowledge-sourcing strategies vary based on the firm size. By accounting for the effects of dynamic search behavior within R&D alliances, our study responds to calls for more research how firms organize their external searches for innovation (Bakker & Knoben, 2014; Dahlander & Gann, 2010; Kale & Singh, 2009; Laursen & Salter, 2014). In our framework, we argue that specific simultaneous diversification patterns of firms are more appropriate to achieving different types of innovation outcomes. In this vein, we expect that firms that manage to organize their external searches with the best potential complementarity mix between the focal firms' resources, capabilities, and innovation objectives and their partners' resources and know-how show superior performance.

As previous literature has noted, there is a lack of openness of firms to their external environment (Chesbrough, 2003b; Laursen & Salter, 2006). Hence, firms that over-focus on internal search activities may generally behave too persistently within their search processes. This myopic and persistent behavior may limit the adaptations of firms to external changes in technology and markets. Therefore, we have introduced a dynamic framework suggesting that firms that effectively adapt their organizational knowledge structure of external linkages according to their current pattern and innovation objectives show superior performance outcomes.

We examine the role of simultaneous partner diversification on different innovation output measures to gain further insights on how external linkages to heterogeneous collaboration partner types affect innovation outcomes. Therefore, our study confirms and extends the previous research on the effects of complementarities between collaboration partner types (Belderbos et al., 2006). In particular, our results highlight the importance of selectivity in collaboration partner types according to specific innovation outcomes and the firm size. For instance, collaboration with scientific partners needs to be complemented to have positive effects on innovation outcomes. By collaborating with scientific partners, firms may gain access to new ideas, scientific workforces and new technology.

However, to make these collaborations effective for innovation outcomes this knowledge and technology need to be complemented with other partner types.

This finding shows that although collaboration with science is an important source for the relative technological potential for SMEs and large firms, this collaboration type needs to be complemented with vertical partner (or vertical and horizontal partner) types to economically exploit radical and incremental innovation outcomes. This need may hint at ineffective appropriation mechanisms in the case of a purely scientific collaboration.

Similar characteristics appear to be valid for horizontal collaborations. Complemented horizontal collaborations with vertical (and scientific) partners are positively associated with innovation outcomes of either type. Along with pure scientific collaborations, pure horizontal collaborations are negatively linked with incremental innovation outcomes. This linkage indicates severe problems with this type of collaboration partner if it is used for innovation activities with only minor product novelty. The innovation monopoly, and hence, the producer rent of a pure horizontal collaboration may not be high enough for incremental innovation activities to fully cover involuntary outgoing spillovers and potential product collusion problems with competitors; these issues may explain the negative effects. These insights regarding horizontal collaboration enhance the discussions about opportunistic behavior versus learning in R&D alliances (Kale, Singh, & Perlmutter, 2000).

Contrary to scientific and horizontal collaborations, vertical collaborations do not need to be complemented with other partner types to exploit innovation performance. Our results particularly emphasize that SMEs can benefit through vertical collaboration; surprisingly, SMEs can also increase their technological potential by means of a vertical collaboration. In line with our expectations, firms do not face tremendous difficulties exploiting and exploring knowledge through collaboration channels with vertical partners.

Focusing on firm size effects, we can state that SMEs show more positive effects of partner diversification associated with innovation outcomes compared to large firms. These findings confirm and extend previous empirical studies (Beck & Schenker–Wicki, 2014) and show that SMEs can substantially benefit from the complementarities gained from external sources of knowledge in their innovation activities. Consequently, the means of partner diversification can allow SMEs to effectively bypass their lack of internal sources compared to large firms.

To examine how firms dynamically adapt their inter-organizational structure of knowledge sourcing and transfer in R&D alliances, we introduce the concept of sequential partner adaptation. Our results reveal that dynamic adaptation is an appropriate measure to confront problems related to path dependency and remaining too persistently within firms' previous knowledge sourcing strategies. In general, we found positive associations between closing down transfer channels from horizontal and scientific partners for incremental innovation performance. These findings demonstrate that those partner types may not provide the most appropriate knowledge sourcing channels to enhance incremental innovation performance. Furthermore, we found positive relationships between opening channels to horizontal partners and radical innovation performance, and between opening vertical channels and all types of innovation outcomes. One exception to these positive relationships concerns our finding for closing down channels to scientific partners. Here, we found negative correlations to the firms' relative technological potential, indicating that knowledge that is derived from scientific collaborations is an important prerequisite for superior technological potential.

Our analysis supports our expectations about the presence of major firm-size effects reflecting the sequential partner adaptations in R&D alliances. Contrary to SMEs, for large firms beginning a scientific collaboration is positively related to the relative technological potential and innovation performance with radical and incremental innovative products. Hence, knowledge sourcing through scientific partners represents an important source of innovation opportunities for large firms. As our results show, large firms can significantly benefit from installing these knowledge transfer channels to scientific partners. Apparently, they have the capabilities to create, manage and retain these new inter-organizational linkages effectively.

Furthermore, our analysis reveals that large firms are able to benefit through closing channels to horizontal partners in terms of incremental innovation performance. Thus, collaboration with competitors may harm large firms if this type of collaboration is associated with projects that only have incremental novelty. Potential collusion in the product output market and involuntarily leaking knowledge to competing firms may explain these results. Contrary to large firms, opening up a horizontal collaboration is positively correlated with radical innovation performance outcomes for SMEs. This correlation indicates that SMEs can benefit from joint innovation activities with competitors to establish new technologies and markets for radical innovations. Given our results, large firms may be more able to derive this result on their own. By reflecting this role of the inclusion and exclusion of horizontal collaboration in the knowledge exchange process in R&D alliances, our study provides new insights in a field where there is a call for more research concerning the potentially opportunistic behavior of competitors in the innovation process (Laursen & Salter, 2014). In summation, our study highlights the importance of simultaneous and sequential partner-type selections in R&D alliances and the importance of adapting collaboration strategies according to changing external environments.

4.5.2 Implications and concluding remarks

The earlier literature on R&D alliances has elaborated on the understanding of how firms organize their external innovation search activities (Katila & Ahuja, 2002; Laursen & Salter, 2006; Laursen & Salter, 2014). However, as suggested by Laursen and Salter (2006) and Bakker and Knoben (2014), more research is needed to better understand the performance implications when firms change their innovative search behavior over time. Our framework explores how sequential changes in firms' search strategies affect their innovation performance. Therefore, we follow Laursen and Salter (2006), who refer to this problem as a “key managerial challenge” (p. 147), and we investigate whether firms that adapt their search behavior over time to respond to major changes in the environment can exhibit better performance compared to those firms that remain persistent in the same search strategy. The present study identified appropriate simultaneous diversification and sequential adaptations strategies to achieve specific innovation outcomes. In this context, the findings of our study should help managers to develop effective re-configurations of firms’ inter-organizational knowledge sourcing structures according to different innovation objectives.

Indeed, our analysis emphasizes that managerial decision makers should be aware of the risk of remaining too persistent and path-dependent within the same search activities. The attitude of non-adapting inter-organizational knowledge exchange strategies could lead to inferior performance. However, our analysis also highlights the need for an appropriate fit between the partners in R&D alliances in terms of their innovation objectives and firm sizes. Thus, a careful evaluation of the potential returns and risks of collaboration is required.

4.5.3 Future research and limitations

Given the nature of our data, we have to be careful about claims of causality. While establishing causality is crucial in order to verify theory, this was not the scope of our project. Furthermore, we strongly believe it is just as important to enhance theories based on correlations, if the later allow analyzing the dynamics that have thus far not received the needed attention in the literature (Arora et al., 2014). However, future avenues of research should account for the selection into collaboration in order to be able to derive stronger claims of causality.

Moreover, this study focuses on the sequential adaptation of the innovative search behavior of firms, and it can only partly capture a full understanding of dynamic firm behavior. Further improvements in data collection could allow researchers to follow a large set of firms over a longer timeframe, which would permit them to take long-term effects into account. Furthermore, having a longer timespan would allow researchers to consider whether experience with the same partner impacts the way firms choose to adapt their partner constellations. Future research could extend the understanding of which mechanisms moderate the adaptation of inter-organization knowledge structures in R&D alliances. For instance, further future studies could analyze the impact of different adaptation strategies across technological trajectories, as such strategies may be highly sector-specific (Fleming & Sorenson, 2001; Katila & Ahuja, 2002). In addition, further research on inter-organizational knowledge creation from different perspectives such as organizational learning, knowledge and intellectual property management is needed to attain an integrated understanding of how firms organize their searches for innovation.

4.6 Appendix

Table 24: Descriptive statistics, industry distribution.

Industry	Number of firms	Percent
1 Construction, mining, energy	496	12.42
2 Consumer goods (food, beverages, tobacco, textiles, clothing)	261	6.54
3 Intermediate goods (paper, printing, chemicals, pharmaceuticals, rubber, plastics, minerals, basic metals)	607	15.20
4 Investment goods (fabricated metals, machinery & equipment, electrical equipment, electronics and optical products, medical instruments, watches, vehicles, and other manufacturing)	1,203	30.13
5 Traditional services (trade, transportation, telecommunications)	750	18.78
6 Knowledge-based services (banking, insurance, information technology & services, technical commercial services)	503	12.60
7 Other services	173	4.33
Total	3,993	100

Table 25: Descriptive statistics, firm size distribution.

Size class	Size class distribution	Number of firms	Percent
1 Small-sized firms	1 – 49	1,918	48.03
2 Medium-sized	50 – 249	1,482	37.11
3 Large-sized	250 – max.	593	14.85
	Total	3,993	100

CHAPTER 5

Concluding remarks

5.1 Summary and conclusions

Innovation policies generate headlines in political agendas, as demonstrated by the Europe 2020 strategy from the European Commission. However, discussions on innovation policies are not only made by policymakers at the very top national or international level but also appear at the local and regional levels. The recent discussions on the foundation of the Swiss innovation park in the Zurich metropolitan area are one example of this vertical permeability of innovation topics.[23] In addition, the frequency with which subjects concerning innovation are discussed appears to grow steadily. Given the challenges of international and national competitiveness, the public pays serious attention to innovation policies, and increasingly, more stakeholders show interest in the design and evaluation of innovation policies.

This dissertation's objective is to advance the comprehension of innovation policies. This thesis is composed of three empirical studies that analyze the role of public innovation policies for firm innovation investments and outcomes. The

[23] More information on the Swiss Innovation Park can be found in Sauter, Geilinger, and Krogh (2014).

objective of this work is not to demonstrate how innovation in firms can be planned in detail by innovation policies, but to outline the basic conditions under which innovation policies may stimulate the generation of innovations in the private sector. In particular, this dissertation contributes to the literature in the following manner.

First, the study in chapter two shows that a public innovation support policy, which directly funds private R&D projects, can help to increase R&D investments in the private sector and to stimulate innovations of a radical nature. This result reveals that public innovation policies are an effective means to confront problems related to market failure in R&D and innovation activities. In addition, and most notably, this study highlights that the public policy under review is effective in orienting R&D efforts in the private sector to socially favorable objectives such as stimulating radical innovation projects.

Second, this thesis, in chapter three, focuses on the relationship between diversity of collaboration partner types and innovation performance. The findings note that firms, and in particular small firms, can benefit from diversity in strategic R&D alliances. However, firms should be aware of decreasing marginal returns from diversity, which indicate that excessive diversity is linked to significant disadvantages, such as high costs and risks, due to increased coordination effort or to ineffective appropriation of joint activities. Although this result points to substantial benefits through diversified R&D collaboration, it also suggests that managers should carefully select their collaboration partners and evaluate the gains and risks of collaboration.

Third, in chapter four, this study investigates the role of simultaneous diversification and sequential adaptation of collaboration partner types within R&D alliances for specific innovation outcomes. In contrast to previous studies, which mainly ignore dynamic aspects, this approach accounts for the sequential adaptation of collaboration patterns; this makes a substantial contribution to the literature on organizational learning. The findings emphasize that firms should not remain extremely persistent within their search activities, and should adapt their inter-organizational knowledge exchange structures to avoid inferior performance. Moreover, this study generally highlights important partner type selection issues and identifies appropriate collaboration strategies in relation to specific innovation outcomes and firm sizes. The knowledge that specific compositions of complementary collaboration partners are more appropriate for certain innovation outcomes should increase the awareness of managers to select appropriate partners in their innovation activities. Overall, we argue that the appropriate selection and use of external partners increases the flexibility to adjust to specific innovation strategies, and thus constitutes a source for change in organizations to adapt to changing environments.

The empirical studies show how innovation policies can stimulate the generation of knowledge and innovations in organizations. By elucidating the pending questions regarding the effects of innovation polices, this thesis provides meaningful implications for decision-makers in politics and organizations; in addition, it enlarges the theoretical reasoning on organizational learning and innovation strategy.

5.2 Limitations and future research

The three empirical analyses presented in this dissertation focus on special issues, and hence only partly grasp how innovation policies affect the generation of knowledge and innovation. To further enlarge the understanding of innovation policies, this section proposes avenues for future research.

The analysis of public innovation policies, such as direct R&D subsidies or R&D collaboration, leads to many questions. As always, the capacity to address the questions depends on the availability and the quality of data. The access to full panel data and the ability to track specific firms over time would allow us to analyze the impact of a subsidy in a before-and-after setting, which enables the use of difference-in-difference estimation methods. Moreover, the availability of information regarding rejected applicants from the subsidy application process would be helpful to refine the analysis to strengthen the empirical findings.

In addition to improving data availability, further areas of future research are also promising. For instance, the analysis could extend to compare the effectiveness of different policy designs such as tax incentives versus direct and indirect subsidies. Although the empirical studies in this dissertation examined how innovation policies affect firm innovation performance, these studies did not investigate the effects of these policies on social welfare. Therefore, future research should also address the role of innovation policies for employment and productivity growth. Hence, in this context, future studies could contribute to the more general debate on the social return of R&D and innovation (Jones & Williams, 1998; Mazzucato, 2014).

Last, as organizations encounter an increasing challenge to adapt to new technologies and markets, it will be interesting to observe how innovation policies manage to adjust to changing environments and organizational needs.

REFERENCES

Abernathy, W. J., & Clark, K. B. 1985. Innovation: Mapping the winds of creative destruction. ***Research policy***, 14(1): 3-22.

Abramovsky, L., Kremp, E., Lopez, A., Schmidt, T., & Simpson, H. 2009. Understanding co-operative innovative activity: evidence from four European countries. ***Economics of Innovation and New Technology***, 18(3): 243-265.

Aghion, P., & Howitt, P. 1992. A Model of Growth Through Creative Destruction. ***Econometrica***, 60(2): 323-351.

Aguirre, D., Post, L., & Hewlett, S. A. 2009. Global talent innovation: Strategies for Breakthrough Performance. ***Strategy + Business***, 56: 39-49.

Ahuja, G., Lampert, C. M., & Novell, E. 2013. The Second Face of Appropriability: Generative Appropriability and Its Determinants. ***Academy of Management Review***, 38(2): 248-269.

Al-Laham, A., Amburgey, T. L., & Baden-Fuller, C. 2010. Who is My Partner and How Do We Dance? Technological Collaboration and Patenting Speed in US Biotechnology. ***British Journal of Management***, 21(3): 789-807.

Amara, N., & Landry, R. 2005. Sources of information as determinants of novelty of innovation in manufacturing firms: evidence from the 1999 Statistics Canada Innovation Survey. ***Technovation***, 25(3): 245-259.

Ancona, D. G., Goodman, P. S., Lawrence, B. S., & Tushman, M. L. 2001. Time: A new research lens. ***Academy of management Review***, 26(4): 645-663.

Angrist, J. D. 1998. Estimating the labor market impact of voluntary military service using social security data on military applicants. ***Econometrica***, 66(2): 249-288.

Argote, L. 2011. Organizational learning research: Past, present and future. ***Management Learning***, 42(4): 439-446.

Argote, L., & Ingram, P. 2000. Knowledge transfer: A basis for competitive advantage in firms. ***Organizational Behavior and Human Decision Processes***, 82(1): 150-169.

Arora, A., Belenzon, S., & Rios, L. A. 2014. Make, buy, organize: The interplay between research, external knowledge, and firm structure. ***Strategic Management Journal***, 35(3): 317-337.

Arrow, K. J. 1962. Economic welfare and the allocation of resources for invention. In R. Nelson (Ed.), ***The Rate and Direction of Inventive Activity***: 609-626: Princeton Univ. Press, Princeton, NJ.

Arrow, K. J., & Lind, R. C. 1970. Uncertainty and the Evaluation of Public Investment Decisions. ***American Economic Review***, 60(3): 364-378.

Arvanitis, A., Ley, M., Seliger, F., Stucki, T., & Wörter, M. 2013. Innovationsaktivitäten in der Schweizer Wirtschaft - Eine Analyse der

Ergebnisse der Innovationserhebung 2011, ***KOF Studien***. Zurich: ETH Zurich.

Arvanitis, A., Seliger, F., Spescha, A., Stucki, T., Veseli, K., & Wörter, M. 2014. Die Entwicklung der Innovationsaktivitäten in der Schweizer Wirtschaft 1997-2012, ***KOF Studien***. Zurich: ETH Zurich.

Arvanitis, S. 2012. How do different motives for R&D cooperation affect firm performance? - An analysis based on Swiss micro data. ***Journal of Evolutionary Economics***, 22(5): 981-1007.

Arvanitis, S., & Bolli, T. 2012. A Comparison of National and International Innovation Cooperation in Five European countries. ***Review of Industrial Organization***: 1-29.

Arvanitis, S., Donze, L., & Sydow, N. 2010. Impact of Swiss technology policy on firm innovation performance: an evaluation based on a matching approach. ***Science and Public Policy***, 37(1): 63-78.

Atuahene-Gima, K. 1995. An Exploratory Analysis of the Impact of Market Orientation on New Product Performance - a Contingency Approach. ***Journal of Product Innovation Management***, 12(4): 275-293.

Atuahene-Gima, K. 2005. Resolving the capability-rigidity paradox in new product innovation. ***Journal of Marketing***, 69(4): 61-83.

Audretsch, D. B. 2003. Standing on the shoulders of midgets: The US Small Business Innovation Research program (SBIR). ***Small Business Economics***, 20(2): 129-135.

Audretsch, D. B., Link, A. N., & Scott, J. T. 2002. Public/private technology partnerships: evaluating SBIR-supported research. ***Research policy***, 31(1): 145-158.

Bakker, R. M., & Knoben, J. 2014. Built to Last or Meant to End: Intertemporal Choice in Strategic Alliance Portfolios. ***Organization Science***.

Battisti, G., Colombo, M. G., & Rabbiosi, L. 2014. Simultaneous Versus Sequential Complementarity in the Adoption of Technological and Organizational Innovations: The Case of Innovations in the Design Sphere. ***Industrial and Corporate Change***.

Bayona, C., Garcia-Marco, T., & Huerta, E. 2001. Firms' motivations for cooperative R&D: an empirical analysis of Spanish firms. ***Research Policy***, 30(8): 1289-1307.

Beck, M., Lopes-Bento, C., & Schenker-Wicki, A. 2014. Radical or incremental: Where does R&D policy hit?, ***UZH Business Working Paper No. 347***. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2507850.

Beck, M., & Schenker–Wicki, A. 2014. Cooperating with external partners: the importance of diversity for innovation performance. ***European Journal of International Management***, 8(5): 548-569.

Becker, W., & Dietz, J. 2004. R&D cooperation and innovation activities of firms - evidence for the German manufacturing industry. ***Research Policy***, 33(2): 209-223.

Belderbos, R., Carree, M., Diederen, B., Lokshin, B., & Veugelers, R. 2004a. Heterogeneity in R&D cooperation strategies. ***International Journal of Industrial Organization***, 22(8-9): 1237-1263.

Belderbos, R., Carree, M., & Lokshin, B. 2004b. Cooperative R&D and firm performance. ***Research Policy***, 33(10): 1477-1492.

Belderbos, R., Carree, M., & Lokshin, B. 2006. Complementarity in R&D cooperation strategies. ***Review of Industrial Organization***, 28(4): 401-426.

Belderbos, R., Carree, M., Lokshin, B., & Sastre, J. F. 2015. Inter-temporal patterns of R&D collaboration and innovative performance. ***The Journal of Technology Transfer***, 40(1): 123-137.

Bercovitz, J. E. L., & Feldman, M. P. 2007. Fishing upstream: Firm innovation strategy and university research alliances. ***Research Policy***, 36(7): 930-948.

Birkinshaw, J., & Crainer, S. 2009. Combine harvesting. ***Business Strategy Review***, 20(4): 20-23.

Bozeman, B. 2000. Technology transfer and public policy: a review of research and theory. ***Research Policy***, 29(4-5): 627-655.

Brannen, M. Y. 2004. When Mickey loses face: Recontextualization, semantic fit, and the semiotics of foreignness. ***Academy of Management Review***, 29(4): 593-616.

Branstetter, L. G., & Sakakibara, M. 2002. When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data. ***The American Economic Review***, 92(1): 143-159.

Brown, J. S., & Duguid, P. 2002. ***The social life of information***. Boston, M.A.: Harvard Business School Press.

Brown, S. L., & Eisenhardt, K. M. 1997. The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. ***Administrative Science Quarterly***, 42(1): 1-34.

Brunswicker, S., & Vanhaverbeke, W. 2015. Open Innovation in Small and Medium-Sized Enterprises (SMEs): External Knowledge Sourcing Strategies and Internal Organizational Facilitators. ***Journal of Small Business Management***, 53(4): 1241-1263.

Cabello-Medina, C., Lopez-Cabrales, A., & Valle-Cabrera, R. 2011. Leveraging the innovative performance of human capital through HRM and social capital in Spanish firms. ***International Journal of Human Resource Management***, 22(4): 807-828.

Caloghirou, Y., Ioannides, S., & Vonortas, N. S. 2003. Research joint ventures. ***Journal of Economic Surveys***, 17(4): 541-570.

Cassiman, B., & Veugelers, R. 2002. R&D cooperation and spillovers: Some empirical evidence from Belgium. ***American Economic Review***, 92(4): 1169-1184.

Cassiman, B., & Veugelers, R. 2006. In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. ***Management Science***, 52(1): 68-82.

Cerchione, R., Esposito, E., & Spadaro, M. R. 2015. The Spread of Knowledge Management in SMEs: A Scenario in Evolution. ***Sustainability***, 7(8): 10210-10232.

Chesbrough, H. W. 2003a. The era of open innovation. ***Mit Sloan Management Review***, 44(3): 35-41.

Chesbrough, H. W. 2003b. ***Open innovation: The new imperative for creating and profiting from technology***. Boston: Harvard Business School Press.

Chesbrough, H. W., Vanhaverbeke, W., & West, J. 2006. ***Open innovation : researching a new paradigm***. Oxford: Oxford University Press.

Chiang, Y. H., & Hung, K. P. 2010. Exploring open search strategies and perceived innovation performance from the perspective of inter-organizational knowledge flows. ***R & D Management***, 40(3): 292-299.

Chung, S., & Kim, G. M. 2003. Performance effects of partnership between manufacturers and suppliers for new product development: the supplier's standpoint. ***Research Policy***, 32(4): 587-603.

Coase, R. H. 1937. The Nature of the Firm. ***Economica-New Series***, 4(16): 386-405.

Cohen, W. M., & Levinthal, D. A. 1989. Innovation and Learning - the 2 Faces of R-and-D. ***Economic Journal***, 99(397): 569-596.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive-Capacity - a New Perspective on Learning and Innovation. ***Administrative Science Quarterly***, 35(1): 128-152.

Colbert, B. A. 2004. The complex resource-based view: Implications for theory and practice in strategic human resource management. ***Academy of Management Review***, 29(3): 341-358.

Colombo, M. G., Laursen, K., Magnusson, M., & Rossi-Lamastra, C. 2011. Organizing Inter- and Intra-Firm Networks: What is the Impact on Innovation Performance? Introduction. ***Industry and Innovation***, 18(6): 531-538.

Cook, S. D., & Brown, J. S. 1999a. Bridging epistemologies: The generative dance between organizational knowledge and organizational knowing. ***Organization science***, 10(4): 381-400.

Cook, S. D. N., & Brown, J. S. 1999b. Bridging epistemologies: The generative dance between organizational knowledge and organizational knowing. ***Organization Science***, 10(4): 381-400.

Coombs, R. 1996. ***Technological collaboration: the dynamics of cooperation in industrial innovation***. Cheltenham, UK: E. Elgar.

CTI. 2011. CTI Activity Report 2011, ***Annual Reports***. Bern: The Commission for Technology and Innovation.

CTI. 2013. CTI in figures Q1-Q2 2013, ***CTI in figures***. Bern: The Commission for Technology and Innovation.

Czarnitzki, D., Ebersberger, B., & Fier, A. 2007. The relationship between R&D collaboration, subsidies and R&D performance: Empirical evidence from Finland and Germany. ***Journal of Applied Econometrics***, 22(7): 1347-1366.

Czarnitzki, D., & Hussinger, K. 2004. The link between R&D subsidies, R&D spending and technological performance: ZEW Discussion Papers.

Czarnitzki, D., & Licht, G. 2006. Additionality of public R&D grants in a transition economy. ***Economics of Transition***, 14(1): 101-131.

Czarnitzki, D., & Lopes-Bento, C. 2014. Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany. ***Industry and Innovation***, 21(5): 380-409.

D'Aspremont, C., & Jacquemin, A. 1988. Cooperative and Noncooperative R&D in Duopoly with Spillovers. ***American Economic Review***, 78(5): 1133-1137.

Dachs, B., Ebersberger, B., & Pyka, A. 2008. Why do firms cooperate for innovation? A comparison of Austrian and Finnish CIS3 results. ***International Journal of Foresight and Innovation Policy***, 4(3): 200-229.

Dahlander, L., & Gann, D. M. 2010. How open is innovation? ***Research Policy***, 39(6): 699-709.

Das, S., Sen, P. K., & Sengupta, S. 1998. Impact of strategic alliances on firm valuation. ***Academy of Management Journal***, 41(1): 27-41.

Dasgupta, P., & Stiglitz, J. 1980. Industrial-Structure and the Nature of Innovative Activity. ***Economic Journal***, 90(358): 266-293.

David, P. A., & Hall, B. H. 2000. Heart of darkness: modeling public–private funding interactions inside the R&D black box. ***Research Policy***, 29(9): 1165-1183.

David, P. A., Hall, B. H., & Toole, A. A. 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. ***Research Policy***, 29(4–5): 497-529.

de Faria, P., Lima, F., & Santos, R. 2010. Cooperation in innovation activities: The importance of partners. ***Research Policy***, 39(8): 1082-1092.

DeBondt, R. 1997. Spillovers and innovative activities. ***International Journal of Industrial Organization***, 15(1): 1-28.

Dehejia, R. H., & Wahba, S. 2002. Propensity score-matching methods for nonexperimental causal studies. ***Review of Economics and Statistics***, 84(1): 151-161.

Dewar, R. D., & Dutton, J. E. 1986. The adoption of radical and incremental innovations: an empirical analysis. ***Management science***, 32(11): 1422-1433.

Dodgson, M. 1991. Technology Learning, Technology Strategy and Competitive Pressures. ***British Journal of Management***, 2(3): 133-149.

Dosi, G. 1988. Sources, Procedures, and Microeconomic Effects of Innovation. ***Journal of Economic Literature***, 26(3): 1120-1171.

Dosi, G. 1997. Opportunities, incentives and the collective patterns of technological change. ***Economic Journal***, 107(444): 1530-1547.

Dosi, G., Freeman, C., Nelson, R., Silverberg, G., & Soete, L. 1988. ***Technical change and economic theory***. London ; New York: Pinter Publishers.

Doz, Y. L., Santos, J., & Williamson, P. J. 2001. ***From global to metanational : how companies win in the knowledge economy***. Boston, Mass.: Harvard Business School Press.

Drejer, I., & Jorgensen, B. H. 2005. The dynamic creation of knowledge: Analysing public-private collaborations. ***Technovation***, 25(2): 83-94.

Easterby- Smith, M., Lyles, M. A., & Tsang, E. W. 2008. Inter- organizational knowledge transfer: Current themes and future prospects. ***Journal of management studies***, 45(4): 677-690.

EC. 2010. EUROPE 2020 A strategy for smart, sustainable and inclusive growth. Brussels: European Commission.

Ettlie, J. E., Bridges, W. P., & O'keefe, R. D. 1984. Organization strategy and structural differences for radical versus incremental innovation. ***Management science***, 30(6): 682-695.

Eurostat. 2013. Science, technology and innovation in Europe: 2013 edition. In E. Union (Ed.). Luxembourg: Publications Office of the European Union.

Faems, D., Van Looy, B., & Debackere, K. 2005. Interorganizational collaboration and innovation: Toward a portfolio approach. ***Journal of Product Innovation Management***, 22(3): 238-250.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. ***Research policy***, 30(7): 1019-1039.

Fritsch, M., & Lukas, R. 2001. Who cooperates on R&D? ***Research Policy***, 30(2): 297-312.

FSO. 2012. Public Funding of Research in Switzerland. Neuchâtel: Federal Statistical Office FSO.

Garcia, R., & Calantone, R. 2002. A critical look at technological innovation typology and innovativeness terminology: a literature review. ***Journal of product innovation management***, 19(2): 110-132.

Gemünden, H. G., Heydebreck, P., & Herden, R. 1992. Technological Interweavement - a Means of Achieving Innovation Success. ***R&D Management***, 22(4): 359-376.

Gerfin, M., & Lechner, M. 2002. A microeconometric evaluation of the active labour market policy in Switzerland. ***Economic Journal***, 112(482): 854-893.

Granstrand, O., Oskarsson, C., Sjoberg, N., & Sjolander, S. 1990. Business strategies for development: Acquisition of new technologies. Chalmers University of Technology.

Greene, W. H. 2003. Econometric analysis, 5th. ***Ed.. Upper Saddle River, NJ***.

Griliches, Z. 1979. Issues in assessing the contribution of research and development to productivity growth. ***The Bell Journal of Economics***: 92-116.

Griliches, Z. 1990. Patent Statistics as Economic Indicators - a Survey. ***Journal of Economic Literature***, 28(4): 1661-1707.

Grilli, L., & Murtinu, S. 2011. Econometric evaluation of public policies for science and innovation: a brief guide to practice. ***Science and Innovation Policy for the New Knowledge Economy***: 60.

Grimpe, C., & Kaiser, U. 2010. Balancing Internal and External Knowledge Acquisition: The Gains and Pains from R&D Outsourcing. ***Journal of Management Studies***, 47(8): 1483-1509.

Gronum, S., Verreynne, M. L., & Kastelle, T. 2012. The Role of Networks in Small and Medium-Sized Enterprise Innovation and Firm Performance. ***Journal of Small Business Management***, 50(2): 257-282.

Gulati, R. 1995. Social structure and alliance formation patterns: A longitudinal analysis. ***Administrative Science Quarterly***, 40(4): 619-652.

Gulati, R., Nohria, N., & Zaheer, A. 2000. Strategic networks. ***Strategic Management Journal***, 21(3): 203-215.

Gulati, R., & Singh, H. 1998. The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. ***Administrative science quarterly***, 43(4): 781-814.

Hagedoorn, J. 1993. Understanding the Rationale of Strategic Technology Partnering - Interorganizational Modes of Cooperation and Sectoral Differences. ***Strategic Management Journal***, 14(5): 371-385.

Hagedoorn, J. 2002. Inter-firm R&D partnerships: an overview of major trends and patterns since 1960. ***Research Policy***, 31(4): 477-492.

Hagedoorn, J., Link, A. N., & Vonortas, N. S. 2000. Research partnerships. ***Research Policy***, 29(4-5): 567-586.

Hall, B. H., & Maffioli, A. 2008. Evaluating the impact of technology development funds in emerging economies: evidence from Latin America. ***The European Journal of Development Research***, 20(2): 172-198.

Heckman, J. J., LaLonde, R. J., & Smith, J. A. 1999. The economics and econometrics of active labor market programs. ***Handbook of labor economics***, 3: 1865-2097.

Henkel, J. 2006. Selective revealing in open innovation processes: The case of embedded Linux. ***Research policy***, 35(7): 953-969.

Henttonen, K., & Ritala, P. 2013. Search far and deep: Focus of open search strategy as driver of firm's innovation performance. ***International Journal of Innovation Management***, 17(03): 1340007.

Henttonen, K., Ritala, P., & Jauhiainen, T. 2011. Exploring open search strategie and their perceived impact on innovation performance - Empirical evidence. ***International Journal of Innovation Management***, 15(03): 525-541.

Hippel, E. v. 1988. ***The sources of innovation***. New York: Oxford University Press.

Hottenrott, H., & Lopes-Bento, C. 2014a. (International) R&D collaboration and SMEs: The effectiveness of targeted public R&D support schemes. ***Research Policy***, 43(6): 1055-1066.

Hottenrott, H., & Lopes-Bento, C. 2014b. R&D Partnerships and Innovation Performance: Can There be too Much of a Good Thing? In ***MSI Discussion paper,*** KU Leuven.

Huizingh, E. K. R. E. 2011. Open innovation: State of the art and future perspectives. ***Technovation***, 31(1): 2-9.

Imbens, G. M., & Wooldridge, J. M. 2008. Recent developments in the econometrics of program evaluation: National Bureau of Economic Research.

Jaffe, A. 1996. Economic Analysis of Research Spillovers: implications for the Advanced Technology Program, ***Advanced Technology Program***. Gaithersburg, MD.

Jaruzelski, B., Loehr, J., & Holman, R. 2012. The global innovation 1000: Making ideas work. ***Strategy + Business***, Winter 2012(69).

Jimenez-Jimenez, D., & Sanz-Valle, R. 2005. Innovation and human resource management fit: an empirical study. ***International Journal of Manpower***, 26(4): 364-381.

Johne, F. A., & Snelson, P. A. 1988. Success factors in product innovation: a selective review of the literature. ***Journal of product innovation management***, 5(2): 114-128.

Jones, C. I., & Williams, J. C. 1998. Measuring the social return to R&D. ***Quarterly Journal of Economics***: 1119-1135.

Jovanovic, B., & Stolyarov, D. 2000. Optimal adoption of complementary technologies. ***American Economic Review***, 90(1): 15-29.

Kaiser, U. 2002. An empirical test of models explaining research expenditures and research cooperation: evidence for the German service sector. ***International Journal of Industrial Organization***, 20(6): 747-774.

Kale, P., & Singh, H. 2009. Managing strategic alliances: What do we know now, and where do we go from here. ***Academy of management perspectives***, 23(3): 45-62.

Kale, P., Singh, H., & Perlmutter, H. 2000. Learning and protection of proprietary assets in strategic alliances: Building relational capital.

Kamien, M. I., Muller, E., & Zang, I. 1992. Research Joint Ventures and Research-and-Development Cartels. ***American Economic Review***, 82(5): 1293-1306.

Kamien, M. I., & Schwartz, N. L. 1978. Self-Financing of an R and D Project. ***The American Economic Review***: 252-261.

Karlsson, C., Friis, C., & Paulsson, T. 2004. Relating entrepreneurship to economic growth. ***The Emerging Digital Economy: Entrepreneurship Clusters and Policy. Springer-Verlag, Berlin***.

Katila, R. 2002. New product search overtime: Past ideas in their prime? ***Academy of Management Journal***, 45(5): 995-1010.

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. ***Academy of Management Journal***, 45(6): 1183-1194.

Katila, R., Rosenberger, J. D., & Eisenhardt, K. M. 2008. Swimming with sharks: Technology ventures, defense mechanisms and corporate relationships. ***Administrative Science Quarterly***, 53(2): 295-332.

Katz, M. L. 1986. An Analysis of Cooperative Research-and-Development. ***Rand Journal of Economics***, 17(4): 527-543.

Kesting, P., Mueller, S., Jorgensen, F., & Ulhoi, J. P. 2011. Innovation and network collaboration: an HRM perspective. ***International Journal of Technology Management***, 56(2-4): 138-153.

Klette, T. J., Møen, J., & Griliches, Z. 2000. Do subsidies to commercial R&D reduce market failures? Microeconometric evaluation studies. ***Research Policy***, 29(4–5): 471-495.

Klevorick, A. K., Levin, R. C., Nelson, R. R., & Winter, S. G. 1995. On the Sources and Significance of Interindustry Differences in Technological Opportunities. ***Research Policy***, 24(2): 185-205.

Knight, F. H. 1921. ***Risk, uncertainty and profit***. Boston and New York,.

Knudsen, M. P., & Mortensen, T. B. 2011. Some immediate - but negative - effects of openness on product development performance. ***Technovation***, 31(1): 54-64.

Kogut, B. 1988. Joint Ventures - Theoretical and Empirical-Perspectives. ***Strategic Management Journal***, 9(4): 319-332.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization science***, 3(3): 383-397.

Koka, B. R., & Prescott, J. E. 2008. Designing alliance networks: The influence of network position, environmental change, and strategy on firm performance. ***Strategic Management Journal***, 29(6): 639-661.

Kotabe, M. 1990. The Relationship between Offshore Sourcing and Innovativeness of United-States Multinational Firms - an Empirical-Investigation. ***Journal of International Business Studies***, 21(4): 623-638.

Laursen, K., & Foss, N. J. 2003. New human resource management practices, complementarities and the impact on innovation performance. ***Cambridge Journal of Economics***, 27(2): 243-263.

Laursen, K., & Salter, A. 2006. Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. ***Strategic Management Journal***, 27(2): 131-150.

Laursen, K., & Salter, A. J. 2014. The paradox of openness: Appropriability, external search and collaboration. ***Research Policy***, 43(5): 867-878.

Lechner, M. 1999. Identification and Estimation of Causal Effects of Multiple Treatments Under the Conditional Independence Assumption: Forschungsinstitut zur Zukunft der Arbeit.

Leiponen, A., & Helfat, C. E. 2010. Innovation Objectives, Knowledge Sources, and the Benefits of Breadth. ***Strategic Management Journal***, 31(2): 224-236.

Lerner, J. 2000. The government as venture capitalist: the long-run impact of the SBIR program. ***The Journal of Private Equity***, 3(2): 55-78.

Levinthal, D., & March, J. G. 1981. A Model of Adaptive Organizational Search. ***Journal of Economic Behavior & Organization***, 2(4): 307-333.

Levinthal, D. A., & March, J. G. 1993. The Myopia of Learning. ***Strategic Management Journal***, 14: 95-112.

Levitt, B., & March, J. G. 1988. Organizational Learning. ***Annual Review of Sociology***, 14: 319-340.

Li, S. X., & Rowley, T. J. 2002. Inertia and evaluation mechanisms in interorganizational partner selection: Syndicate formation among US investment banks. ***Academy of Management Journal***, 45(6): 1104-1119.

Lichtenthaler, U. 2008. Open innovation in practice: An analysis of strategic approaches to technology transactions. ***Ieee Transactions on Engineering Management***, 55(1): 148-157.

Lichtenthaler, U. 2011. Open Innovation: Past research, Current Debates, and Future Directions. ***Academy of Management Perspectives***, 25(1): 75-93.

Lin, Z., Yang, H. B., & Demirkan, I. 2007. The performance consequences of ambidexterity in strategic alliance formations: Empirical investigation and computational theorizing. ***Management Science***, 53(10): 1645-1658.

Lind, J. T., & Mehlum, H. 2010. With or Without U? The Appropriate Test for a U- Shaped Relationship. ***Oxford Bulletin of Economics and Statistics***, 72(1): 109-118.

Loof, H., & Heshmati, A. 2002. Knowledge capital and performance heterogeneity: A firm-level innovation study. ***International Journal of Production Economics***, 76(1): 61-85.

Lundvall, B.-Å. 1992. User-producer relationships, national systems of innovation and internationalization, ***National systems of innovation: towards a theory of innovation and interactive learning***: xiii, 342 p. London: Pinter Publishers.

Madsen, E. L., Clausen, T. H., & Ljunggren, E. 2008. ***Input, output and behavioural additionality: concepts and relationships***. Paper presented at the Druid Conference Paper, Copenhagen.

March, J. G. 1991. Exploration and Exploitation in Organizational Learning. ***Organization Science***, 2(1): 71-87.

March, J. G., & Simon, H. A. 1958. Organizations.

Martin, S. 1994. Private and social incentives to form R & D joint ventures. ***Review of Industrial Organization***, 9(2): 157-171.

Martin, S. 2002. Spillovers, appropriability, and R&D. ***Journal of Economics***, 75(1): 1-32.

Martin, S., & Scott, J. T. 2000. The nature of innovation market failure and the design of public support for private innovation. ***Research Policy***, 29(4–5): 437-447.

Mazzucato, M. 2014. ***The entrepreneurial state: debunking public vs. private sector myths*** (Revised edition. ed.). London: Anthem Press.

Metcalfe, J. S. 1994. Evolutionary Economics and Technology Policy. ***Economic Journal***, 104(425): 931-944.

Meuer, J., Rupietta, C., & Backes-Gellner, U. 2015. Layers of co-existing innovation systems. ***Research Policy***, 44(4): 888-910.

Miotti, L., & Sachwald, F. 2003. Co-operative R&D: why and with whom? An integrated framework of analysis. ***Research Policy***, 32(8): 1481-1499.

Mohammed, S., & Nadkarni, S. 2011. Temporal diversity and team performance: The moderating role of team temporal leadership. ***Academy of Management Journal***, 54(3): 489-508.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17: 77-91.

Murray, M. P. 2006. The bad, the weak, and the ugly: Avoiding the pitfalls of instrumental variables estimation. Available at SSRN 843185.

Nelson, R. R. 1959. The Simple Economics of Basic Scientific-Research. ***Journal of Political Economy***, 67(3): 297-306.

Nelson, R. R., & Winter, S. G. 1982. ***An evolutionary theory of economic change***. Cambridge, Mass.: Belknap Press of Harvard University Press.

Nieto, M. J., & Santamaria, L. 2007. The importance of diverse collaborative networks for the novelty of product innovation. ***Technovation***, 27(6-7): 367-377.

Nonaka, I. o., & Takeuchi, H. 1995. ***The knowledge-creating company: how Japanese companies create the dynamics of innovation***. New York: Oxford University Press.

Nooteboom, B. 1999. ***Inter-firm alliances : analysis and design***. London ; New York: Routledge.

Ocasio, W. 1997. Towards an attention-based view of the firm. ***Strategic Management Journal***, 18: 187-206.

OECD. 1992. ***Proposed guidelines for collecting and interpreting technology innovation data. Oslo Manual.*** Paris: Organisation for Economic Co-operation and Development.

OECD. 1997. ***Proposed guidelines for collecting and interpreting technological innovation data: Oslo Manual***. Paris: Organisation for Economic Co-operation and Development.

Parmigiani, A., & Mitchell, W. 2009. Complementarity, capabilities, and the boundaries of the firm: the impact of within-firm and interfirm expertise on concurrent sourcing of complementary components. ***Strategic Management Journal***, 30(10): 1065-1091.

Patel, P., & Pavitt, K. 1997. The technological competencies of the world's largest firms: complex and path-dependent, but not much variety. ***Research policy***, 26(2): 141-156.

Pavitt, K. 1988. International Patterns of Technological Accumulation. In N. Hood, & J.-E. Vahlne (Eds.), ***Strategies in Global Competition***. London: Croom Helm.

Penrose, E. T. 1959. ***The theory of the growth of the firm***. New York,: Wiley.

Pisano, G. P. 1990. The R&D Boundaries of the Firm: An Empirical Analysis. ***Administrative Science Quarterly***, 35(1): 153-176.

Porter, M. E. 1980. ***Competitive strategy : techniques for analyzing industries and competitors***. New York: Free Press.

Porter, M. E. 1990. ***The competitive advantage of nations***. New York: Free Press.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. ***Administrative Science Quarterly***, 41(1): 116-145.

Raisch, S., & Birkinshaw, J. 2008. Organizational ambidexterity: Antecedents, outcomes, and moderators. ***Journal of management***.

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. 2009. Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. ***Organization Science***, 20(4): 685-695.

Richardson, G. B. 1972. The Organisation of Industry. ***The Economic Journal***, 82(327): 883-896.

Ritala, P., & Hurmelinna-Laukkanen, P. 2009. What's in it for me? Creating and appropriating value in innovation-related coopetition. ***Technovation***, 29(12): 819-828.

Rivkin, J. W. 2000. Imitation of complex strategies. ***Management science***, 46(6): 824-844.

Romer, P. M. 1990. Endogenous Technological Change. ***Journal of Political Economy***, 98(5): S71-S102.

Rosenbaum, P. R., & Rubin, D. B. 1985. Constructing a Control-Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. ***American Statistician***, 39(1): 33-38.

Rosenfeld, S. A. 1996. Does cooperation enhance competitiveness? Assessing the impacts of inter-firm collaboration. ***Research Policy***, 25(2): 247-263.

Rubin, D. B. 1977. Assignment to Treatment Group on the Basis of a Covariate. ***Journal of Educational and Behavioral statistics***, 2(1): 1-26.

Sakakibara, M. 2001. The diversity of R&D consortia and firm behavior: Evidence from Japanese data. ***Journal of Industrial Economics***, 49(2): 181-196.

Salter, A. J., & Martin, B. R. 2001. The economic benefits of publicly funded basic research: a critical review. ***Research policy***, 30(3): 509-532.

Sampson, R. C. 2005. Experience effects and collaborative returns in R&D alliances. ***Strategic Management Journal***, 26(11): 1009.

Sampson, R. C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. ***Academy of Management Journal***, 50(2): 364-386.

Sauter, B., Geilinger, N., & Krogh, G. v. 2014. Building for the Current and Next Generations: The Swiss Innovation Park. Zurich: Swiss-American Chamber of Commerce.

Schuler, R. S., & Jackson, S. E. 1987. Linking Competitive Strategies with Human Resource Management Practices. ***Academy of Management Executive (08963789)***, 1(3): 207-219.

Schuler, R. S., & Jackson, S. E. 2007. ***Strategic human resource management*** (2nd ed.). Malden, MA: Blackwell.

Schumpeter, J. A. 1912. ***Theorie der wirtschaftlichen entwicklung***. Leipzig: Duncker & Humblot.

Smith, J. A., & Todd, P. E. 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? ***Journal of Econometrics***, 125(1-2): 305-353.

Smith, M. H. 2005. Uncertainty and the adoption of complementary technologies. ***Industrial and Corporate Change***, 14(4): 639-650.

Smith, R. J., & Blundell, R. W. 1986. An exogeneity test for a simultaneous equation Tobit model with an application to labor supply. ***Econometrica: Journal of the Econometric Society***: 679-685.

Sofka, W., & Grimpe, C. 2010. Specialized search and innovation performance - evidence across Europe. ***R & D Management***, 40(3): 310-323.

Soo, C. W., Devinney, T. M., & Midgley, D. F. 2007. External knowledge acquisition, creativity and learning in organisational problem solving. ***International Journal of Technology Management***, 38(1): 137-159.

Spence, M. 1984. Cost Reduction, Competition, and Industry Performance. ***Econometrica***, 52(1): 101-121.

Teece, D. J. 1982. Towards an Economic-Theory of the Multiproduct Firm. ***Journal of Economic Behavior & Organization***, 3(1): 39-63.

Teece, D. J. 1986. Profiting from Technological Innovation - Implications for Integration, Collaboration, Licensing and Public-Policy. ***Research Policy***, 15(6): 285-305.

Teece, D. J. 1992. Competition, Cooperation, and Innovation - Organizational Arrangements for Regimes of Rapid Technological-Progress. ***Journal of Economic Behavior & Organization***, 18(1): 1-25.

Teece, D. J., Pisano, G., & Shuen, A. 1997. Dynamic capabilities and strategic management. ***Strategic management journal***, 18(7): 509-533.

Teirlinck, P., & Spithoven, A. 2013. Research collaboration and R&D outsourcing: Different R&D personnel requirements in SMEs. ***Technovation***, 33(4-5): 142-153.

Tether, B. S. 2002. Who co-operates for innovation, and why - An empirical analysis. ***Research Policy***, 31(6): 947-967.

Tobin, J. 1958. Estimation of Relationships for Limited Dependent-Variables. ***Econometrica***, 26(1): 24-36.

Tsang, E. W. K. 2000. Transaction cost and resource-based explanations of joint ventures: A comparison and synthesis. ***Organization Studies***, 21(1): 215-242.

Tseng, M. M., & Piller, F. T. 2003. ***The customer centric enterprise: advances in mass customization and personalizaton***. Berlin: Springer.

Tushman, M. L., & Anderson, P. 1986. Technological discontinuities and organizational environments. ***Administrative science quarterly***, 31(3): 439-465.

Tushman, M. L., & Smith, W. 2002. Organizational technology. ***Companion to organizations***, 386: 414.

van de Vrande, V., de Jong, J. P. J., Vanhaverbeke, W., & de Rochemont, M. 2009. Open innovation in SMEs: Trends, motives and management challenges. ***Technovation***, 29(6-7): 423-437.

Vuola, O., & Hameri, A. P. 2006. Mutually benefiting joint innovation process between industry and big-science. ***Technovation***, 26(1): 3-12.

Wallin, M. W., & Von Krogh, G. 2010. Organizing for Open Innovation:: Focus on the Integration of Knowledge. ***Organizational Dynamics***, 39(2): 145-154.

Wallsten, S. J. 2000. The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. ***Rand Journal of Economics***, 31(1): 82-100.

Way, S. A., Tracey, J. B., Fay, C. H., Wright, P. M., Snell, S. A., Chang, S., & Gong, Y. 2012. Validation of a Multidimensional HR Flexibility Measure. ***Journal of Management***.

Weigelt, C. 2009. The Impact of Outsourcing New Technologies on Integrative Capabilities and Performance. ***Strategic Management Journal***, 30(6): 595-616.

Whitley, R. 2002. Developing innovative competences: the role of institutional frameworks. ***Industrial and Corporate Change***, 11(3): 497-528.

Williamson, O. E. 1975. ***Markets and hierarchies, analysis and antitrust implications : a study in the economics of internal organization***. New York: Free Press.

Williamson, O. E. 1985. ***The economic institutions of capitalism: firms, markets, relational contracting***. New York: Free Press.

Williamson, O. E. 1989. Transaction cost economics. In R. Schmalensee, & R. D. Willig (Eds.), ***Handbook of industrial organization***. New York: Elsevier Science Pub. Co.

Winkelmann, R., & Boes, S. 2006. ***Analysis of microdata***: Springer.

Wooldridge, J. M. 2010. ***Econometric analysis of cross section and panel data***: MIT press.

Wozniak, G. D. 1987. Human-Capital, Information, and the Early Adoption of New Technology. ***Journal of Human Resources***, 22(1): 101-112.

Zeng, S. X., Xie, X. M., & Tam, C. M. 2010. Relationship between cooperation networks and innovation performance of SMEs. ***Technovation***, 30(3): 181-194.

CURRICULUM VITAE

PERSONAL INFORMATION

Name:	Mathias Oliver Hermann Beck
Date of Birth:	January 10th, 1980
Nationality:	German

EDUCATION

2/2010 – present	PhD studies in Management & Economics at the University of Zurich, Switzerland
9/2004 – 7/2005	Fellow at Luiss Guido Carli in Rome, Italy, Department of Economics and Business
10/2000 – 4/2009	M.Sc. in Industrial Engineering and Management (Diplom Wirtschaftsingenieur) at the Karlsruhe Institute of Technology, Germany
10/1999 – 8/2000	Studies in Medicine, University of Tübingen, Germany
9/1990 – 6/1999	Abitur (Secondary School) at Staatliches Gymnasium Hechingen, Germany

PROFESSIONAL EXPERIENCE

2/2010 – present	Research and Teaching Assistant at the Chair for Performance Management (Prof. Dr. Dr. h.c. Andrea Schenker-Wicki), Department of Business Administration, University of Zurich, Switzerland
5/2007 – 1/2009	Student Assistant at the HECTOR School of Engineering and Management, Karlsruhe Institute of Technology, Germany
10/2006 – 1/2007	Intern at Porsche Consulting GmbH, Bietigheim-Bissingen, Germany
8/1999 – 8/2004	Intern at gambro dialysatoren GmbH, Hechingen, Germany

TEACHING

2/2010 – present	Lecturer at the Faculty of Economics, Business Administration and Information Technology, University of Zurich, Switzerland
8/2010 – 10/2015	Teaching Skills Certificate Program UZH